Explaining Firms' Heterogeneity in Productivity and Wages: Ownership, Innovation and Size

Chiara Criscuolo

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Abstract

Micro data have provided invaluable contributions to a better understanding of the drivers of, and factors affecting, wages, productivity and productivity growth. The literature in this area has highlighted both ownership and innovative activity as two factors that consistently seem to affect productivity and its dynamics at the micro level and the empirical regularity that larger firms pay higher wages. This thesis provides evidence on these issues. In the first chapter I investigate the implications of ownership concentration and the presence of financial institutions for productivity, using both accounting data and detailed data on shareholdings for a panel of quoted UK companies. I control for unobserved firm fixed effects and the endogeneity of inputs and ownership using GMM estimation. The second chapter considers whether nationality of ownership affects productivity. The analysis challenges previous evidence of a foreign ownership advantage in the UK by showing that the foreign advantage is by and large a multinational advantage, except for US firms. In addition, longitudinal analysis disentangles the sources of the US and MNE productivity advantage. The third chapter examines the hypothesis that multinational firms have access to larger knowledge stocks and quantifies how much multinationals' innovative success is due to higher innovation expenditure and how much to access to their intra-firm worldwide pool of information. The fourth chapter matches information on innovative activity with production data to investigate the link between innovation expenditure, knowledge flows and productivity growth. The results confirm the importance of knowledge flows for innovation and of innovation for productivity growth. The final chapter of the thesis investigates the empirical regularity that larger establishments pay higher wages. The longitudinal estimates demonstrate that positive effects of firm size on wages persist after controlling for observed and unobserved worker, firm and match specific characteristics and correcting for non-random mobility of workers.

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Declaration

No part of the thesis has been presented to any university for any degree

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Chapter 1

Introduction

The existence of differences in wages, productivity levels and growth rates not only across industries but also within industries is now a well known phenomenon in the literature. A second strong empirical result has emerged from the empirical evidence that this differences are not only large but also persistent over time. The evidence on the drivers of this heterogeneity is less clear cut.

Understanding the sources of heterogeneity in firms' productivity and wages is a key question. This is because ultimately productivity can explain differences in countries' performance, competitiveness and living standards. As for wages, which affect income inequality, it is important to understand how much they depend not only on workers qualities and characteristics but also on firms' characteristics and wage policies.

Micro data has proved invaluable not only for a better description of firms' heterogeneity in innovative activity, productivity and wages but also for a deeper insight into the drivers and understanding of the mechanisms that relate institutional and technological factors to productivity, growth and wage differentials.

Bartelsman and Doms (2000) and Tybout (2000) recent surveys of longitudinal micro level productivity studies identify four factors that consistently seem to affect productivity and its dynamics at the microlevel: technology and human capital; government regulations that affect incentives to innovate; (international) competition on product markets that make firms learn more quickly about new production methods and technologies and firm ownership and management of firms. The first four chapters of this thesis attempt to analyse some of these issues, whereas the fifth broadens the analysis to one particular aspect of heterogeneity in firms' wages: size wage differentials.

Indispensable to applied research is the availability of good data. I was fortunate enough to get access to unique datasets at the firm, plant and worker level. Indeed, the order of the thesis chapters mirror the descendent order in terms of the level of analysis conducted: from companies in chapter 2, to plants in chapter 3 to 5 and workers in chapter 6.[1]

The next two chapters study the relationship between ownership and productivity, where ownership is considered in two ways: Chapter 2 considers the impact of ownership concentration and identity; Chapter 3 focuses on foreign and multinational status of businesses.

In the next chapter I investigate the empirical relationship between ownership structure and productivity using accounting and detailed shareholdings' ownership data for a panel of quoted UK companies. After controlling for unobserved firm fixed effects and the endogeneity of the inputs using GMM estimation, concentrated ownership has a positive effect on productivity as predicted by principal agent models. Moreover, I find that the presence of financial institutions as large block shareholders has an additional positive effect on productivity. The rationale underlying the work in this first chapter is that separation between ownership and control does affect firm performance because of principal agent problems. Agency theories predict that since managers are utility maximisers, their interests may conflict with shareholders' interest. When shareholders have small stakes or have very diversified portfolios, a free-rider problem arises: no shareholder has an incentive in participating in costly monitoring or in engaging in active 'voice'; this leads to relatively weak control on the part of shareholders on managers, who do not behave as profit maximisers (Grossman and Hart, 1980). Large shareholders, on the other hand, have both a strong incentive to invest in acquiring information and monitoring the activity of managers and have the voting power to control managers (Shleifer and Vishny, 1986).

This chapter uses a unique dataset obtained from matching the financial infor-

[1]Chapter 3; 4 and 5 contain statistical data from the Office of National Statistics (ONS) which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data.

mation from Datastream with shareholdings' information from the CDA Spectrum Database. This database is unique in that it contains very detailed time series information for a cross section of listed companies on the concentration and the identity of the firm's owners. This allows, for the first time, the use of longitudinal ownership information to estimate the relationship between ownership concentration, the presence of financial institutions as owners and productivity in levels. Previous studies only had cross-sectional ownership information and studied the relationship between ownership and productivity growth (Nickell et al., 1997 and Curcio, 1994), this is the first study that relates changes in shareholders structure to changes in firm productivity, certainly for the UK and to our knowledge in the literature. Finally, this chapter contributes to the policy debate on the efficiency of financial institutions as shareholders. In fact, institutional portfolios tend to be highly diversified. Thus, a high proportion of institutional ownership tends to be associated with a less concentrated ownership structure, and institutional investors are seen as relatively passive shareholders in the exercise of corporate control, preferring exit rather than voice; this would lead to a lower level of productivity, according to our model. On the other hand, institutional investors tend to be better informed than other investors, and therefore could choose to invest in companies with a higher productivity potential, this could result in the data overestimating the positive correlation between institutional ownership and productivity. Thus, with cross-sectional data and without additional information on firm's ownership structure it is very difficult to identify the presence of a causal relationship between presence of financial institutions as shareholders, controlling for the size of their investment, and productivity. In this chapter I find that the presence of financial institutions as large block shareholders has an additional positive effect on productivity over and above the effect of ownership concentration. This result seems particularly relevant for Europe, where the scope for private insurance and non-state pension funds is becoming more and more pressing, but might be policy relevant in less developed countries where privatisation and the development of a full size stock market is still taking place.

The third chapter considers whether ownership nationality affects productivity.[2] The heterogeneity between foreign and domestic firms is the subject of many empirical papers in developed and developing countries. The confirmed advantage of

[2]This chapter draws on joint work with Ralf Martin.

foreign owned plants relative to domestic has been used as justification for subsidies to attract foreign direct investment. However, the comparison of foreign direct investors and domestic firms is flawed in that it does not compare like with like and this is particularly so in the UK, who is both amongst the largest receiver of FDI and a very active foreign direct investors.

Indeed, previous UK studies using firm level data find that foreign owned firms are more productive than domestic ones. This could reflect a foreign advantage or an omitted variable bias: foreign firms are by definition multinational enterprises (MNEs), and MNEs are typically more productive than non-MNEs.

The first contribution of this chapter consists of a discrimination between these hypotheses. Using a newly available dataset – the Annual Inquiry into Foreign Direct Investment (AFDI) – it identifies, for the first time, domestic MNEs in a large scale UK plant level productivity dataset. The results show, that the foreign productivity advantage found in previous UK studies is mostly a multinational advantage except for US owned plants that are the productivity leaders.

This latter result is also a contribution to the literature in that it qualifies previous findings by Doms and Jensen (1998): in their study using US data they also find that controlling for multinationality of the firms, US firms are the productivity leaders. However, since they identify US MNE firms on US data they cannot rule out that the leadership of US MNE owned plants is the consequence of a home advantage. The results of this chapter establish the leadership of US MNEs in Britain, which shows that the US MNE advantage found by Doms and Jensen is not a home advantage.

The third contribution of this chapter is to exploit the longitudinal nature of the ARD-AFDI panel to investigate the source of the US and multinational advantages. Indeed, the theory of multinational enterprises (MNEs) attributes the superiority of MNEs to intrinsic transferable superior firm specific assets – such as better management techniques and better production technology – that they can share with their affiliates (Dunning, 1981, Helpman, 1984 and Markusen, 1995). At the same time, if multinational firms have better access to credit markets and enjoy a lower cost of capital, their advantage might also be strengthened if overvalued firms in the source country decide to use low cost capital to target firms abroad not affected by the same stock market bubble (the 'cheap capital' view of FDI, Baker et al. (2004)). This might explain a better ability to "cherry pick" and take over the best firms in the host country. Finally, we can test a third hypothesis, that investing abroad might lead to improvement in the efficiency of MNEs domestic plants, through reverse learning effects (Branstetter, 2001).

The longitudinal analysis – inspired by the methodologies recently applied in labour economics on matched employer-employees data – shows that the MNE productivity advantage is driven by sharing superior firm specific knowledge among affiliated plants and in the ability to takeover already productive plants; however no evidence is found that firms' decision to invest abroad leads to short-term improvement in the productivity of domestic plants. The additional US advantage lies in the better ability to takeover the most productive plants, and indeed this seems in line with evidence for the same time period of a temporary overvaluation on the American stock market.

Chapter 4 represents a further investigation of the causes of the MNEs superiority.[3] It extends the analysis to the innovative activity of firms. Indeed, existing evidence, econometric and from case-studies, shows that MNEs are the most innovative firms, in terms of R&D spent and patents held. This is in line with the theory of multinationals which asserts that in order to compete successfully in a foreign market MNE firms must have some intangible asset that is easily shared among affiliates and that is too costly to transact in the market place (Hymer, 1970).

The chapter focuses on the hypothesis from the trade literature that globally engaged firms-either multinationals or exporters-have access to larger knowledge stocks. Estimates of knowledge production functions for a cross-section of UK plants covering their operations from 1998 to 2000 show that globally engaged firms do generate more ideas than their purely domestic counterparts. This is not just because they use more researchers. It is also because they have access to a larger stock of ideas through two main sources: their upstream and downstream contacts with suppliers and customers, and, for multinationals, their intra-firm worldwide pool of information.

The study contributes to three different streams of the literature. Firstly, it contributes to the trade literature, because trade models of multinationals (Markusen, 2002, for an extensive treatment or Carr et al., 2001, for an abridged summary) make

[3]This chapter draws on joint work with Jonathan Haskel and Matthew Slaughter.

the crucial assumption that these firms are particularly knowledge intensive relative to purely domestic firms. Indeed, in this "knowledge capital" model multinationals arise via FDI largely because of the desire (and ability) to deploy firm-specific knowledge assets in multiple countries despite the co-ordination and set-up costs of multi-plant production. There is evidence of this cross-border intra-firm knowledge transfer (e.g. Mansfield and Romeo, 1980). However, this literature does not quantify the relative importance of these different knowledge inputs (e.g. R&D scientists and knowledge flows) using a knowledge production function framework as we do here.

Secondly, this chapter adds to the debate in the macro growth literature in that it might contribute to shed light on the existence (or the lack there of) of a single global stock of knowledge "immediately available to be used in any economy" anywhere in the world (Jones, 2002 or for a similar argument see Parente and Prescott, 1994). Although there is widespread acceptance of this framework of a production function for new ideas, there is very little evidence on its empirical validity. Indeed one of the open questions that remain in this field is the shape of the idea production function (Jones, 2003). The estimates in chapter three may help to provide some of the key parameters to answer this question.

Finally, this research adds to the existing Industrial Organisation literature on innovation. The paper represents the first attempt to use survey data on innovation to analyse the heterogeneity in the innovative activity between domestic, exporter and multinational corporation in the UK. Indeed Chapter 3 fits into a relatively recent literature that analyses the 'black box' of the innovation process at the firm level (Griliches and Pakes, 1980) using as innovation output, beside patents, direct product and process innovations indicators from firm level surveys.

Chapter 5 extends the analysis to integrate the knowledge production function approach used in chapter 4 into a system that estimates the determinants of innovation investments as well as the production of new knowledge, and then models the relationship between innovation and productivity growth. Chapter 5 performs this by using the information on innovation outputs and inputs from the Community Innovation Surveys, and matching it with production data from the ARD panel, for the manufacturing sector. Our approach is to use product and process innovation output measures and relate them to the inputs of the knowledge production function, and to productivity growth. This is a notable advantage relative to much of the previous literature. I can actually estimate parameters of interest in the knowledge production function and I can relate to productivity growth successful innovation outcomes, rather than innovation inputs, such as R&D, or innovation outputs, such as patents, that only capture a small part of the innovation activity. The approach adopted is similar in spirit to the models of Crépon, Duguet and Mairesse (2000) and Klomp and van Leeuwen (2001). Relative to this research, our model adds the following features. Firstly, contrary to the models of Crépon et al. and Klomp and van Leeuwen, I explicitly consider the knowledge production function for process innovation; secondly, I introduce both product and process innovations, novel and incremental, in a total factor productivity growth regression that allows for imperfect competition and non constant returns to scale. Finally, I try to control for possible endogeneity bias using information from past innovation surveys.

Finally, the analysis in chapters 4 and 5, hopefully, contributes to future research from a different aspect. The present study does for the first time use the Community Innovation Survey matching it to both the AFDI and the ARD for productivity analysis. This has required a careful and time consuming process of data cleaning and matching, that hopefully corrected some of the initial inconsistencies of the data that, was the source of the dismissal by other UK researchers. I hope that the analysis presented here confirms that the data does have limitations but shows consistent patterns.

Chapter 6 also exploits a unique dataset, the German *Institut für Arbeitsmarkt und Berufsforschung* (IAB) employment panel, which might be seen as a predecessor of matched employer-employees datasets, to investigates why large establishments pay higher wages.

The dataset is unique because it measures wages and separations very precisely, and I have a continuous and precise measure of plant's size. For each worker-firm pair in the data I can independently follow the work history of the worker and the business life of the plant, its size, its past growth, its birth and closure. The data contains very useful information for studying the research question of size-wage differentials: beside a continuous measure of size, it has industry classification, location, the skill composition of the plant and its age.

An attempt to account for the size premium using observable worker and plant characteristics through level estimation meets with limited success. Therefore, I apply fixed effect and first difference models correcting for endogeneity and self-selection issues. In the longitudinal analysis, the size wage differential is still sizeable and is quite similar to level estimates. I find that the wage change closely resembles the differential estimated in the level regression. The empirical findings demonstrate that positive effects of firm size on wages persist after controlling for observed and unobserved worker and firm characteristics. They suggest that although each of the explanations of size-wage differentials can account for some of the observed variation in worker wages, none can fully unravel the observed employer size-wage differentials. In the end, the unexplained premium remains large and significant. The chapter contributes to the existing empirical literature on size-wage differentials because of the richness of the data, but because it purges the estimate of the size elasticity from unobserved fixed firm and individual characteristics, controlling for the endogeneity of size and the non-randomness of job mobility.

Chapter 7 concludes. It reviews the key findings of this research and suggesting some policy implications. It discusses some aspects deserving further attention and illustrates the next steps that will be built on the work conducted in this PhD. It also suggest some ideas for future research.

Chapter 2

Ownership structure and productivity

2.1 Introduction

The basic neoclassical economic model predicts that ownership should have no effect on firm performance (Modigliani and Miller, 1958). However, as early as Adam Smith in the Wealth of Nations (1776), economists recognised that the separation of ownership and control potentially leads to a conflict of interest between the managers, who control the firm, and the owners of the firm. At the beginning of the thirties Berle and Means (1932) suggested that an inverse correlation should be observed between the diffuseness of shareholdings and firm performance. Since the work of Berle and Means the consequences of the separation of ownership and control have been the subject of a lively debate in the economic and financial literature. More recently, Jensen and Meckling (1976) developed a principal agent model to explain the modern corporation and the costs of outside equity and show formally how the allocation of shares among insiders and outsiders can influence the value of the firm.

Agency theories predict that large shareholders have a positive effect on corporate performance because they have both a strong incentive to invest in acquiring information and in monitoring the activity of managers and have the voting power to control managers (Shleifer and Vishny, 1986). When shareholders have small stakes or have very diversified portfolios, a free-rider problem arises: no shareholder has an incentive in participating in costly monitoring or in engaging in active 'voice'; this leads to relatively weak control on the part of shareholders on managers, who do not behave as profit maximisers (Grossman and Hart, 1980). An alternative view of the role of ownership structure is proposed by Demsetz (1983). He challenges the hypothesis that diffuseness of ownership has a negative impact on firm performance. He argues that the ownership structure of a corporation should be thought of as an endogenous outcome of decisions that reflect the influence of shareholders. A diffuse ownership structure, if brought about by shareholders, should maximize shareholder profit, so that there should be no systematic relation between variations in ownership structure and variations in firm performance. The empirical studies about the relation between ownership structure and firm performance seem to have yielded conflicting results.

The research has mainly looked at corporate governance and the effect of the separation of ownership and control for firm value, with empirical applications mainly focused on the US (Demsetz and Lehn (1985), Himmelberg et al. (1999) and Morck et al. (1988), to cite a few). Moreover, these empirical studies about the relationship between ownership structure and firm performance seem to have yielded conflicting results.

Fewer studies have explored the relationship between corporate performance and (financial) institutional ownership. The reason why this is relevant is that financial institutions are likely to to be professional investors with better knowledge about historical returns and thus have different preferences for risk and returns from individual shareholders. They will look for diversification of their portfolio to diminish risk since they are accountable for the management of funds. Thus, a high proportion of institutional ownership tends to be associated with a less concentrated ownership structure. Indeed, there are dissenting opinions about institutional shareholder activism. It is argued that institutions are passive shareholders because they lack the resources and the incentives to be involved in corporate strategy of all their investments, their individual share stakes are frequently quite small and they refrain from acquiring private information, preferring 'exit' rather than 'voice'. This, according to agency theories would lead to a negative correlation between firm performance and presence of financial institutions. At the same time, institutional investors tend to have greater expertise and be better informed than other investors, and could therefore choose to invest in companies with a higher productivity potential. Moreover, they are likely not to have any ties to incumbent management. Thus, they can monitor managers more efficiently than small atomistic shareholders. Again, empirical studies on the role of institutional investors appear contradictory (see for example Pound, 1988, Brickley et al., 1988, and McConnell and Servaes, 1990, for the US; and Leech and Leahy, 1991, Curcio, 1994, and Nickell et al., 1997 for the UK).

This chapter investigates if differences in productivity can be related to differences in the structure of firms' share ownership, both in terms of its concentration and presence of financial institutional investors. It uses a panel of UK quoted companies to study the role of concentrated ownership and large stockholdings by institutional owners for productivity.

This research makes the following contribution to the existing literature. It investigates if differences in the structure of firms' share ownership can be related to differences in productivity, rather than market value.

Productivity captures different aspects of firm performance from market value. First, any productive input that is fully compensated in the market may be related to productivity but unrelated to market value. Second, productivity captures current activity, while market value reflects future profits and associated anticipated value. Thus, the factors that affect current activity may be very different from those affecting future profit streams. One might argue that some factors inherently lead to a negative correlation between market value and current productivity. For example, a business with a new idea carrying a high market value may be actively expanding and investing in physical and human capital. Adjustment costs may imply that such a firm exhibits low current productivity (Abowd et al., 2002a). Third, most studies use as dependent variable Tobin's Q.[1] The numerator of this variable, being the market value of the firm, is affected by the investors optimism, or pessimism, and expectations on future events, including the business' outcomes and thus partly reflects the value investors assign to a firms intangible assets. On the other hand, the denominator of Q, the estimated replacement cost of the firms tangible assets, does not include investments the firm has made in intangible assets. The firm's future outcomes are treated as if they can be generated from investments made only

[1] Defined as the ratio of a firm's market value to the replacement costs of its physical assets.

in tangible capital. Thus, performance comparisons based on Tobin's Q of firms that rely in differing degrees on intangible capital would be distorted.

Relative to previous empirical work in the UK, which analyses the relationship between ownership structure and productivity growth (Curcio, 1994, and Nickell, Nicolitsas and Dryden,1997), we can use much more detailed longitudinal information on beneficial share ownership structure. Both of these two previous studies, Curcio (1994) and Nickell et al. (1997), had to rely on the implicit assumption that ownership remains constant at a particular level over the sample period and that it can be treated as exogenous in a first-differenced equation. Such assumptions are unlikely to hold over long periods. By contrast this study, exploits the longitudinal information on changes in ownership structure, available in the data, to identify the causal link between ownership and productivity. Also, the information on share ownership structure of the company is much more detailed than in previous studies: the dataset, a panel for a sample of listed UK companies over the 1985-1997 period, contains information on the identity of beneficial owners behind most nominee accounts for all registered shareholdings above 0.25% of a firm's total equity if there are less than 99 shareholdings above this threshold, or for the largest 99 registered shareholdings above 0.25%. This allows me to investigate not only the role of ownership concentration but also to identify differences between type of owners. Finally, for the identification of a causal effect of ownership on productivity, I need to correct for the endogeneity of inputs when estimating production functions and consider the possible endogeneity of the ownership structure. To deal with both problems, I use the difference-GMM estimator, as introduced by Arellano and Bond (1991) that was adopted in both the Curcio and Nickell et al. studies but I also test the robustness of the results using the GMM system estimator as described by Blundell and Bond (1998). This estimator overcomes finite sample bias due to weak instruments in autoregressive models with persistent series with small time periods of the Arellano and Bond GMM estimator.

Our findings show that, controlling for endogeneity, ownership concentration has a positive effect on productivity, thus supporting the predictions of principal-agents models. Secondly, I find that the presence of financial institutional owners among the larger shareholders has a positive effect on productivity. These results are robust to the presence of serially uncorrelated measurement error and to alternative specifications and estimation methods.

The chapter is structured as follows: in Section 2.2 I review previous UK studies on the relationship between ownership and productivity (growth). Section 2.3 describes the data and the sample. In section 2.5 I describe the empirical model and our preferred estimation method. Section 2.6 reports the main results. Section 2.7 concludes. Appendix A reports further details on the data, the sample and the ownership measures used.

2.2 Evidence on ownership and productivity from previous UK studies

There seems to be a relatively small empirical literature which examines the effects of ownership and control structures on the productivity of the firm.

Previous papers that have investigated the relationship between the ownership structure and productivity growth in the UK are Curcio (1994) and Nickell et al. (1997). Curcio studies the relationship between managerial ownership of shares and firm performance, measured as market valuation (Tobin's Q) and as total factor productivity (TFP) growth using an unbalanced panel of 389 UK manufacturing companies, all with dual structure of voting rights,[2] over the 1972-86 period. The only ownership information available is the holdings of each director of the companies for the year 1981 or 1982. The study looks at the consequences of a disparity between equity and votes ownership of the managers and finds that managers owning more votes than equity has a strong negative effect on TFP growth; managerial stakes between 5% and 100% have a weak positive effect on productivity growth and concentration of voting power with respect to the equity capital of the firm has a weak negative effect on TFP growth. As stressed by the author himself, this result does not imply that voting concentration and productivity are not related in levels; the analysis is constrained by the lack of time variation in the concentration index. Given the lack of longitudinal information on the ownership structure of the firm, the study has to rely on the implicit assumption that management ownership

[2] According to Curcio's definition, firms might have a dual structure of voting rights if they have issued different types of ordinary shares with different voting rights, share with different rights to dividends or if they have issued preference share with attached voting rights.

remained constant at the 1981-82 level for the whole time a company is present in the sample. Curcio justifies this assumption since *managerial ownership is generally believed to be quite a sticky variable.* A similar assumption underlies the study by Nickell et al..

Nickell, Nicolitsas and Dryden concentrate mainly on the issue of the degree of substitution between shareholder control, product market competition and financial pressure as discipline devices for non-profit maximising managers using a panel of UK manufacturing firms over the period 1982 to 1994. Information on shareholder control is available for only 125 of the 582 companies included in the sample. Following Cubbin and Leech (1983) and Leech and Leahy (1991) , firms are classified as 'owner-controlled' if a dominant shareholder owns a specified fraction of the company and as being 'manager-controlled' if the shareholdings are diversified. In particular, shareholder control is included in the regression as a dummy variable that equals one if a dominant shareholder has a α (equals 90% or 95%) probability of winning a shareholder' vote if all other shareholders are assumed to vote randomly. Since this variable is available only for one year, the authors can only study the effect of the ownership structure, assumed to remain constant at the beginning of the period level, on the productivity growth of the firm. The results indicate that the presence of a dominant external shareholder has a significant and negative effect if the dominant shareholder is an external non-financial institution whereas it has a strong positive (3.2%) impact effect on productivity growth if the external shareholder is a financial institution, who can substitute for competition to discipline managers. This study has three main weaknesses: firstly the ownership information is only available for 125 firms. Secondly, it is only available for one year, thus hindering the authors to look at the relationship between ownership and productivity in levels. Thirdly, the measure of 'control' used hinges on the validity of the probability voting model as developed by Cubbin and Leech (1983) and the assumption of independent behaviour of shareholders when voting. Finally, a problem of selection is introduced, since only firms that were 'alive' in 1981-82 - i.e. the only year for which the ownership information is available- can be considered.

2.3 The data and the sample

2.3.1 The data

The study uses a panel of UK quoted companies over the period 1985-1997[3]. The data consists of companies accounting information from Datastream International matched with share ownership information from the CDA Spectrum database.

The CDA Spectrum database contains the identity of beneficial owners behind most nominees accounts for all registered shareholdings above 0.25% of a firm's total equity (if there are less than 99 shareholdings above this threshold) or for the largest 99 registered shareholdings above 0.25%. This means that it covers a large proportion of a firm's equity including relatively small shareholdings.

Beneficial owners are classified within 8 categories: 'individuals'; 'private clients of banks'; 'non-financial companies'; 'Sepon Ltd'[4]; 'pension funds'; 'insurance companies'; 'other financial institutions'[5] and 'others'. This last category includes Church Commissioners, local Government bodies, Universities and foreign government agencies; thus this category mostly include 'non-financial institutions'. Nominee holdings that cannot be attributed to any beneficial owner are treated as unidentified.

The ownership information was matched with accounting data from Datastream international for the firms in the sample for the 1985-1997 period. In the empirical analysis I always use the nearest available shareholding information preceding the beginning of the accounting period.[6]

The data presents two main drawbacks. Firstly, it only covers companies that are quoted on the Stock Exchange. Quoted companies are mainly large firms. Thus, our study might be affected by sample selection problems. Since I do not have information on listing decisions, I am not able to correct for this source of sample selection bias[7]. Also, the fundamental principal agent problem is likely to arise in

[3]The data was made available by Steve Bond at the Institute for Fiscal Studies

[4]the Stock Exchange clearing company, indicating a shareholding that is in the process of being sold

[5]In the empirical analysis the three categories 'pension funds'; 'insurance companies' and 'other financial institutions' are aggregated in the category 'financial institutions'.

[6]in four cases the ownership is recorded within 27 days from the beginning of the accounting year

[7]However, the panel is unbalanced so that exiting firms are kept in the dataset

public companies. Secondly, I cannot identify whether shares are held by managers; in particular I cannot distinguish whether individual shareholders are somehow related to managers of the firm or to the founder of the firm.[8].

2.3.2 Sample

Since for the analysis I need at least 4 consecutive years of available information, I discard those companies for which information is available for 3 years or less. I also drop those firms for which information on employment and wages is missing. Moreover, I drop those observations for which real value added, real sales, employment, total real wages or capital grow more than 300% or decrease by more than 75% from one accounting year to the next.[9] Finally, I break the series for those firms, whose accounting period was more than 400 or less than 300 days due to changes in end date of the accounting year. This leaves me with an unbalanced panel of 268 firms[10] and 2395 observations over the period 1985 to 1997.

Appendix A.1.2 provides more details on the structure of the unbalanced panel: table A.2 describes the structure of the sample by number of annual observations per company and table A.3 reports the number of companies per year.

2.4 Descriptive statistics

Table 2.1 reports measures of ownership concentration: column 1 for the whole sample, column 2 for the sample of small firms and column 3 for the sample of large firms.[11] The table shows that larger firms have both a much higher financial institutional ownership and a more dispersed ownership.

Row 1 measures concentration as the proportion of firm's total equity owned by the largest shareholder, row 2 by the largest five and row 3 by the largest ten shareholders. Using any of the three measures I can confirm that shareholding ownership

[8]Some studies have attempted to account for possible connections between shareholders and management by matching shareholders and directors' surnames. I are not able to follow this procedure using the information available since the category 'individuals' is constructed as a residual category as shown in table A.1 in appendix A.1.1

[9]These outliers could be due to mismeasurement problems or to mergers and acquisitions

[10]my unit of analysis is a firm, for which I have four consecutive years of information. Each time there is a break in the series I consider it as being a new firm.

[11]Small (large) firms are defined according to whether the number of employees in the first year the firm is in the sample is below (above) the median firm in that year.

is much more concentrated in smaller companies. Row 4 reports an alternative measure of concentration: the Herfindahl index of ownership concentration with an average value of 0.06; this value reflects the fact that ownership is quite dispersed in companies quoted on the London Stock Exchange. This is consistent with previous studies and macro evidence from ONS. This is further confirmed in row 5 where I consider the proportion of shareholdings held in block greater or equal to 5%: this amounts to 38.14% in small firms and to a mere 17.45% in large firms.

The second panel (rows 6 to 9) report statistics on the identity of large shareholders. Rows 6 and 7 summarise the presence of financial institutions and individuals, respectively, among the largest 5 shareholders. Column 1 shows that financial institutions are much more likely to be among the largest five shareholders than individuals and this is much more so in larger firms as shown in column 3. The opposite is true in smaller firms as shown by comparing row 6 and 7 in column 2. A similar pattern emerges from row 8 and 9, when I look at the proportions of blockholdings greater or equal to 5% in the hands of financial institutions (row 8) and individuals (row 9). However, the difference between the presence of financial institutions and individuals among large blockholders is much less evident relative to row 6 and 7.

Table A.4 in Appendix A.2 describes the distribution of beneficial share ownership between the 7 classes of owners for all firms in the sample, for small and large firms. The last row of the table shows that on average, I identify the ultimate owners for 66.32% of the total equity; this means that 66.32% of shares is in the hand of the largest 99 shareholders, or in holdings of more than 0.25%. This confirms the high dispersion of share ownership in our sample. A comparison of panels 2 (columns 3 and 4) and 3 (columns 5 and 6) shows differences in ownership structures between small and large firms. Firstly, individual shareholders hold a much larger proportion of equity in smaller firms, whereas financial institutions are more present in larger companies. Secondly, the percentage of total identified equity, i.e. equity owned in blocks larger than 0.25% or by the largest 99 largest shareholders, is much higher in smaller firms. This indicates a higher concentration of ownership in this group. Table A.5, also confirms that in our sample ownership is very dispersed looking at the distribution of out preferred six measures of ownership concentration and identity of large owners. Examining the six panels I observe that in large firms ownership

Table 2.1: Ownership concentration measures

		(1)	(2)	(3)
		all	small	big
(1)	top1	13.68	16.69	11.11
		(12.11)	*(10.92)*	*(12.47)*
(2)	top5	34.74	43.17	27.53
		(17.55)	*(15.69)*	*(15.76)*
(3)	top10	47.08	57.53	38.13
		(19.05)	*(15.85)*	*(16.88)*
(4)	Herfindahl	0.06	0.07	0.04
		(0.08)	*(0.08)*	*(0.09)*
(5)	block5	27.00	38.14	17.45
		(21.74)	*(19.19)*	*(19.10)*
(6)	top5ind	26.24	39.83	14.60
		(33.36)	*(34.76)*	*(27.17)*
(7)	top5inst	50.59	38.49	60.95
		(33.51)	*(30.81)*	*(32.24)*
(8)	block5inst	9.28	11.84	7.08
		(11.64)	*(13.58)*	*(9.12)*
(9)	block5ind	10.93	18.25	4.66
		(17.81)	*(20.45)*	*(12.06)*

Notes: Reported statistics are unweighted averages and in italics in parentheses unweighted standard deviations calculated on the unbalanced panel of 268 firms and 2395 observations over the 1985-1997 period. Small (large) firms have in the year they enter the sample a number of employees lower (higher) than the median firm in that particular year. Row 1 refers to top1, the proportion of equity owned by the largest shareholder, row 2 to top5, the largest five shareholders and row 3 to top10, the largest 10 shareholders. Row 4 reports summary statistics for the Herfindahl index of concentration, calculated as described in the appendix A.1.2. Row 5 the proportion of shares held in blocks greater or equal to 5%. In the second panel: in row 6 top5ind measures the proportion of shares held by the largest 5 shareholders in the hand of individuals. In row 7 top5inst refers to the same measure but for financial institutions. Row 8 and 9 report the proportion of shares held by financial institutions (row 8) and individuals (row 9) in blockholdings greater or equal to 5 %.

is more dispersed and that the presence of financial institutions among the largest shareholders is much stronger.

Table A.7 describes the ownership pattern in our sample over the period 1985 to 1997. The table shows that there are changes in ownership structure over the period under study. This is important for two main reasons: the estimation strategy relies on the time series variation in the ownership variables for identification of causal effects; secondly, the table confirms that the assumption that ownership is constant over time cannot be maintained in our sample. Rows 1 to 5 show that there is not a clear monotonic pattern in the concentration of ownership; this pattern is reflected in all the measures considered. After an initial increase with a peak in 1991 there is a decline in concentration. Rows 6 to 12 show the pattern of concentration taking into account the identity of the shareholders. Rows 6 to 9 show the pattern of individual and institutional ownership among the largest 5 and 10 shareholders: the statistics confirm the steady decline of individual ownership and the increase in financial ownership. Row 10 confirms the same pattern looking at the proportion of equity held by the largest individual shareholder. Finally, rows 11 and 12 show that the decline in individual ownership is confirmed when looking at the proportion of holdings held in blocks larger than 5% of total equity.

This table, therefore, confirms that the assumption implicit in previous empirical work (Curcio and Nickell et al.) that the ownership structure remained constant at a fixed level for the whole time a company is present in the sample, cannot be applied to our sample, in particular when the identity of the shareholders is considered.

A possible concern with table A.7 is that the ownership changes may simply reflect changes in the composition of the unbalanced panel, rather than changes within survival firms. I investigate this issue further. I concentrate on the pattern of ownership concentration in a balanced panel of surviving firms over the period 1987 to 1993, this sample includes 130 firms. In the top panel I look at the pattern of the variable 'top5', i.e. the proportion of outstanding equity held by the largest five shareholders. The pattern is very similar in the unbalanced and balanced panel, however the level of ownership concentration is much smaller in the balanced panel, this is likely due to the composition of the latter. In the balance panel I include firms that are present in the sample from 1987 to 1993, i.e. I systematically exclude exitors. In our sample, exit happens because of takeover or bankruptcy; the probability of either event is higher for smaller firms. Thus, in the balanced subsample I select larger firms that, as shown in previous descriptive statistics, have a less concentrated ownership structure.

In the bottom panel I describe the pattern of 'inst5', i.e the proportion of shareholdings held by institutions in blocks larger than 5% of the total equity. Figure 2.1 shows that the pattern and the level of this variable in the balanced subsample is in this case very is similar to that of the whole sample.

These descriptive results are in line with evidence found in previous empirical studies (Leech and Leahy (1991); Bettoni et al. (2000), Bond and Chennels (2000) and Bond et al. (1997)) estimates of ownership patterns for the UK stock market. The ONS report on Share Ownership confirms a downward trend in the presence of individuals since 1960s and a sharp increase in the presence of foreign investors[12] and shows that pension funds experiences a slow growth in the 1980s and since 1992 the proportion of shares has slowly fallen, probably due to increased maturity and a diversification into bonds. This patterns are accompanied by an increased dispersion of shareholdings in the UK.

Since the empirical analysis will focus on the role of ownership concentration, table 2.2 shows the characteristics of firms with a higher level of ownership concentration in their first year in the sample[13]. The table shows that firms with a higher ownership concentration are smaller, less productive, both in terms of labour and total factor productivity, and have less output per employee ratio. They are also less capital intensive.

2.5 The empirical model and estimation method

The empirical approach consists of estimating an augmented production function as reduced form of a system of equations which includes a technological relationship and a set of behavioural equations, which are then substituted out. I therefore

[12] that are part of the other institutions category according to our classification

[13] I divide our sample into two groups by ownership concentration,defining firms with high (low) concentration those with an above (below) median level of equity held by the largest five shareholders in the first year they are in the sample

Figure 2.1: Trend of ownership structure in the sample

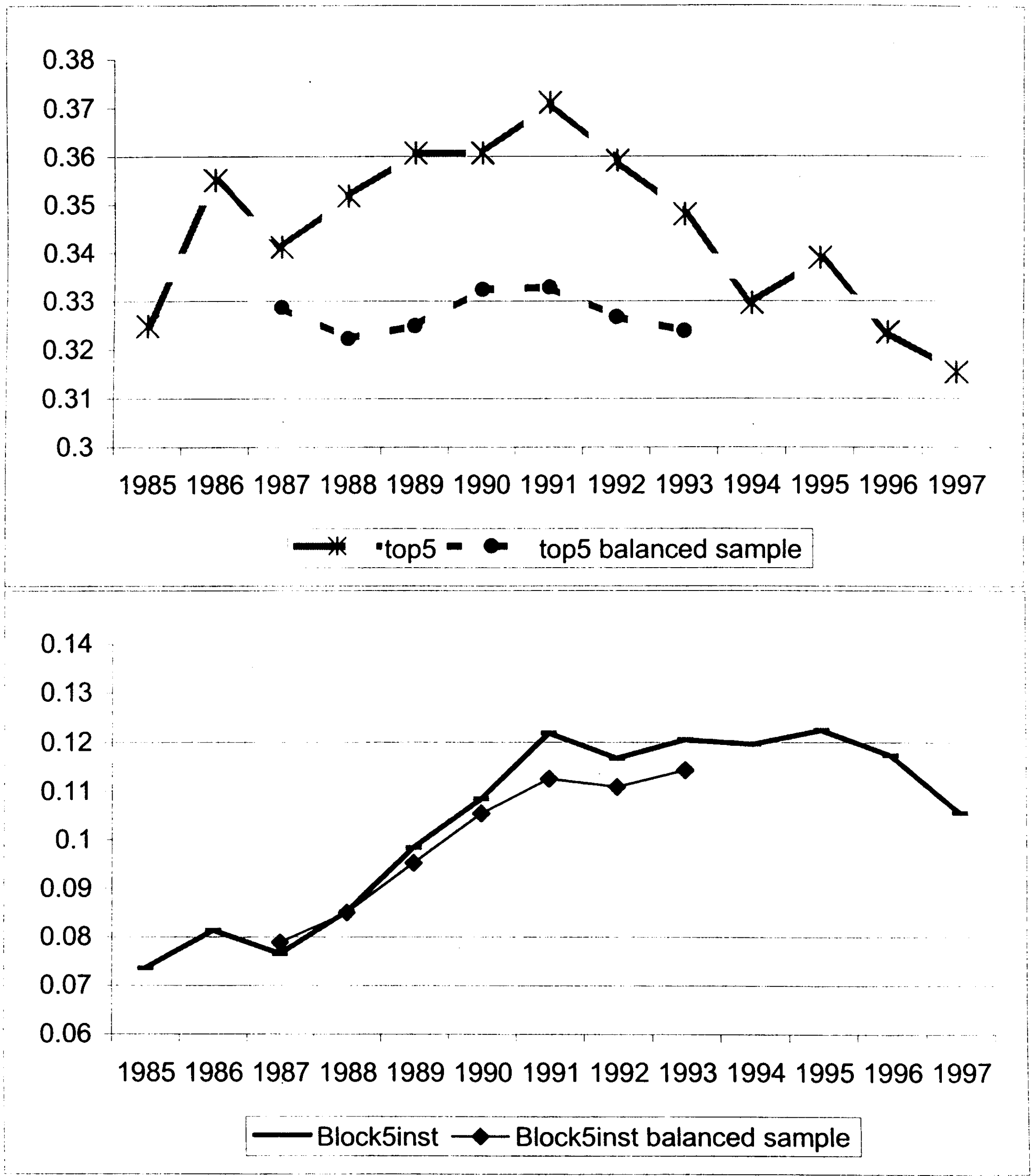


Table 2.2: Characteristics of firms with low and high level of ownership concentration

	EMP	*VA/EMP*	*TFP*	*SALES/EMP*	*K/EMP*
low concentration	1868.50	19.85	8.38	63.91	12.81
	(12358.59)	*(22.01)*	*(8.37)*	*(87.39)*	*(18.58)*
high concentration	482.50	18.89	8.00	58.61	12.24
	(1198.39)	*(21.26)*	*(9.13)*	*(98.12)*	*(25.09)*
whole sample	928.50	19.50	8.15	62.02	12.38
	(6195.50)	*(21.59)*	*(8.79)*	*(93.31)*	*(22.18)*

Notes::The table refers to the a sample of 268 firms with 2,395 observations. Figures reported are mean and standard deviation in parentheses. Firms are defined as low(highly) concentrated if the proportion of shares held by the largest 5 shareholders is below (above) the sample median in the first year the firm is in the sample.

estimate an augmented standard neoclassical production technology:

$$Y_{it} = Y[A_{it}F(N_{it}, K_{it})] \tag{2.1}$$

and

$$A_{it} = e^{Own_{it}\delta_t\eta_i v_{it} m_{it}} \tag{2.2}$$

Where Y represents firm's output, A represents a Hicks' neutral shift parameter, N represents the number of employees, K the capital stock of the firm calculated using the perpetual inventory method, Own_{it} is a measure of ownership concentration and/or identity of shareholders, δ_t is a time specific component which I model with time dummies, η_i is a time-invariant firm-specific component, m_{it} is a (serially uncorrelated) measurement error component. Assuming Cobb-Douglas technology I obtain:

$$A_{it}F(N_{it}, K_{it}) = A_{it}N_{it}^{\alpha}K_{it}^{\beta} \tag{2.3}$$

As shown by Blundell and Bond (1998), one can account for lags in adjustments of the production process and for unobserved characteristics that are persistent over time but are not fixed, such as managerial ability, by allowing for the error component v_{it} to be (first order) autoregressive[14].

Plugging equation 2.2 in equation 2.3 and taking logarithms I obtain the esti-

[14]This specification has an additional implication that it is important in justifying the estimation method described below. The presence of lags of adjustments to shocks is a behavioral theory that justifies the use of lagged levels of inputs as instruments for their growth rates, this answer a general criticism in Griliches and Mairesse.

mating equation, where lower case letters denote logarithms, i.e. $x = ln(X)$:

$$y_{it} = \alpha_0 + \alpha n_{it} + \beta k_{it} + \gamma Own_{it} + \delta_t + \eta_i + v_{it} + m_{it} \tag{2.4}$$

where I allow for the autoregressive component in the error term:

$$\begin{aligned} v_{it} &= \rho v_{i(t-1)} + e_{it} \\ |\rho| &< 1 \end{aligned} \tag{2.5}$$

and y_{it} is the logarithm of output of firm i at time t, n_{it} is log number of employees and k_{it} is log capital stock. The residual of the estimated production function represents the relative total factor productivity of the companies in the sample. Plugging (2.5) in (2.4) and rearranging I can rewrite the model using the following dynamic representation as:

$$\begin{aligned} y_{it} = {} & \alpha n_{it} - \rho\alpha n_{i(t-1)} + \beta k_{it} - \rho\beta k_{i(t-1)} + \gamma Own_{it} - \rho\gamma Own_{i(t-1)} \\ & + \rho y_{i(t-1)} + (\delta_t - \rho\delta_{t-1}) + \eta_i(1-\rho) + e_{it} + m_{it} - \rho m_{i(t-1)} \end{aligned} \tag{2.6}$$

or

$$\begin{aligned} y_{it} = {} & \pi_1 n_{it} + \pi_2 n_{i(t-1)} + \pi_3 k_{it} + \pi_4 k_{i(t-1)} + \pi_5 Own_{it} + \pi_6 Own_{i(t-1)} \\ & + \pi_7 y_{i(t-1)} + \delta_t^* + \eta_i^* + \omega_{it} \end{aligned} \tag{2.7}$$

subject to three non-linear common factor restrictions: $\pi_2 = -\pi_1\pi_7$; $\pi_4 = -\pi_3\pi_7$ and $\pi_6 = -\pi_5\pi_7$. I test and impose these common factor restrictions using minimum distance.

Labour and capital are potentially correlated with all of the error components, time varying and firm specific fixed effects, and possibly affected by serially uncorrelated measurement error and therefore are treated as endogenous. To overcome these problems of endogeneity in dynamic panel models, a common approach is GMM estimation as proposed by Arellano and Bond (1991) and adopted in previous UK studies on the effects of ownership structure on productivity (e.g. Curcio (1994) and Nickell et al. (1997)). To control for the presence of firm fixed effects it takes first differences,[15] then performs an instrumental variable estimation, where it uses lagged values of the endogenous regressors as instruments for the differenced equations. Since consistency of the GMM estimator requires lack of second order correlation and significant negative first order serial correlation in the differenced residuals, tests for first (m1 in the tables) and second order (m2 in the tables) correlation are performed. The overall validity of the instruments is tested using a Sargan test of overidentifying restrictions.

The GMM estimator has been criticised in the literature, in particular for production function estimation by Griliches and Mairesse and Blundell and Bond, because regressors' first-differences are likely to be only weakly correlated with their lagged levels.[16] Indeed in highly persistent time series, as it is the case here as shown by table A.6 in the Appendix A.2, and/or when the number of time series observations is moderately small, lagged levels will be poor instruments for first-differences, resulting in finite sample bias and poor precision of the estimates.

Blundell and Bond propose a system GMM estimator for data with a large number of firms observed for a small number of time periods. The system estimator uses lagged first differences of the series as instruments for equations in levels, in addition to the lagged levels as instruments for the equations in first differences.[17] In respect to the GMM first-difference estimator, the GMM system estimator has been shown (by Monte-Carlo simulations) to perform better in terms of efficiency and finite sample bias. The validity of the additional instruments depends on initial stationarity restrictions[18] that must be tested using a Difference Sargan test for over-identifying restrictions[19]. The power of the Sargan test for overidentifying

[15]Nickell (1981) shows that the within-group estimator yields downward biased estimates in dynamic panels. Although the bias tends to zero as T approaches infinity, it remains significant in small samples.

[16]Griliches and Mairesse note that *many economic variables evolve in a random walk like fashion at the micro level.* I thus consider the case when x_t follows a random walk to illustrate the weak instrument problem. $x_t = x_{t-1} + \varepsilon_t$ where ε_t is assumed to be white noise and $\Delta x_t = \varepsilon_t$, which results in x_{t-1} not being correlated with Δx_t. Note that this does not entail that Δx_t is not correlated with x_t.

[17]Arellano and Bover (1995) also show that efficiency of the differenced GMM estimator can be improved using the equations in levels. The system GMM approach as also the advantage of estimating parameters of regressors that do not vary over time.

[18]These restrictions are: mean stationarity of the process; that the initial observation is drawn from the same underlying data generating process and that the first differences of the instrumented regressors are not correlated with the fixed effects, i.e. constant correlation between regressors and fixed effects (Blundell et al., 2000).

[19]Since I treat labour and capital as endogenous I instrument them with their value lagged two

restrictions in the context of dynamic panel data models may be low (see Bowsher, 2002). Moreover it might be difficult, as it is indeed the case in our sample, to find valid additional instruments.

However, Blundell and Bond show that first-differenced GMM estimates of production function parameters after imposing constant returns to scale (CRS) are very close to the system GMM estimates: imposing constant returns to scales reduces the weak instruments bias problems in the first-differenced GMM estimates discussed above. Blundell and Bond suggest that this is likely to be due to the lower persistency or the capital-labour ratio series relative to the levels of either capital or labour series. They therefore justify the practice of imposing CRS in the first-differenced GMM estimator, even though the restriction is rejected in order to obtain reasonable capital coefficient estimates.

Thus, our preferred method for estimating the production function is the panel data GMM differenced estimator as proposed by Arellano and Bond (1991) imposing constant returns to scale[20] and implemented using the program DPD98 (Arellano and Bond, 1998). When reporting the results I always report coefficients and standard errors robust to heterogeneity from the first-step estimation, which has been found to be less efficient (Blundell et al., 2000) but more reliable for conducting inference.

A problem when estimating the effect of ownership on productivity is the correlation between ownership and the error term component of the augmented production function. The main contribution of this study is the use of the time variation of firms' ownership structure to attempt to identify a causal effect of ownership on productivity.

One possible source of endogeneity of Own_{it} is its correlation with the unobserved company specific effect: $cov(\eta_i, Own_{it}) \neq 0$[21]. As long as these different unobserved characteristics are stable over the period of time in which the firm is present in

and earlier periods. In the robustness checks I use as additional instruments for the equation in levels $\Delta(\Delta va_{t-1})$ and assume that the firm specific effects are uncorrelated with the second-differences of the endogenous variable va_t used as instruments for the equations in levels.

[20]The assumption of constant returns to scales in this context is equivalent to the assumption: $\alpha + \beta = 1$.

[21]There might be a possible self-selection process of shareholders into companies with different productivity levels. Shareholders with different access to information, for example, may sort themselves into firms that are systematically different.

the sample they can be differenced out and the time variation in the ownership information used to identify the causal effect of ownership on productivity.

A second source of endogeneity maybe caused by measurement error in the ownership variable. If I allow for possible measurement error, then $E(v_{it}|Own_{it}) \neq 0$, and ownership is endogenous. Only ownership variables lagged three periods and before are valid instruments for the equations in differences, since $E(v_{i,t} - v_{i,(t-1)}|Own_{i,(t-1-n)}) = 0 \ \forall \ n \geq 2$.

In the empirical analysis I control for the correlation of the ownership variable with firm fixed effects. Moreover in our preferred specification I assume that ownership is predetermined[22] However in the robustness checks I show that our results are robust to controlling for measurement error.

2.6 Results

Table 2.3 reports coefficients estimates from an OLS regression of a static model[23] of ownership concentration on productivity. Ownership structure is assumed uncorrelated with firm fixed effects and with idiosyncratic shocks. The top panel reports the effect of different measures of ownership concentration on labour productivity: the estimated coefficients are negative and significantly so for all measures used but top1. In the bottom panel I control for capital intensity: the estimated effect of ownership concentration is negative, but not significantly different from zero, for all measures of concentration used.

These results seem to contradict the predictions of principal agents models. How can this be explained? I have already shown in section 2.4 that ownership of smaller firms is generally more concentrated. This fact is confirmed in table 2.4 where I report the OLS estimates of a regression of ownership concentration (using the same measures used in table 2.3) on size measured as log employment. In all columns the coefficient is strongly significant and negative.

The heterogeneity between large and small firms must be accounted for if one

[22] i..e I assume that ownership structure is determined by past history and is not measured with error. Formally: $E(v_{it}|Own_{it}) = 0$ but $E(v_{is}|Own_{it}) \neq 0 \ \forall s < t$. Lagged values of this variable are valid instruments for the equation in differences, since $E(v_{i,t} - v_{i,(t-1)}|Own_{i,(t-n-1)}) = 0 \ \forall \ n \geq 1$.

[23] The static model does not allow for an autoregressive component in the error term and OLS does not control for the endogeneity of capital and labour.

Table 2.3: Effect of ownership concentration on productivity. OLS estimates
(Dependent variable is log real value added per employee)

	(1) top1	(2) top5	(3) top10	(4) block5	(5) block5inst	(6) block5ind
Concentration	-0.1951	-0.3938	-0.4131	-0.3415	-0.4741	-0.3408
	(0.1730)	*(0.1258)*	*(0.1135)*	*(0.0987)*	*(0.2249)*	*(0.1258)*
R-squared	0.05	0.07	0.08	0.08	0.06	0.07
	(1) top1	(2) top5	(3) top10	(5) block5	(6) block5inst	(7) block5ind
Concentration	0.0395	-0.0872	-0.0963	-0.1032	-0.1878	-0.0853
	(0.1188)	*(0.0885)*	*(0.0828)*	*(0.0725)*	*(0.1611)*	*(0.0944)*
$Ln(K/N)$	0.3370	0.3320	0.3305	0.3302	0.3328	0.3326
	(0.0253)	*(0.0258)*	*(0.0261)*	*(0.0258)*	*(0.0255)*	*(0.0257)*
R-squared	0.05	0.07	0.08	0.08	0.06	0.07

Notes: The sample is an unbalanced panel of 268 firms. The observations used are 2,127 from 1986 to 1997. All regressions are estimated by OLS and include a set of time dummies. Asymptotic standard errors robust to heteroscedasticity and autocorrelation of arbitrary form are reported in italics. In all columns the Dependent variable is log real value added. Concentration variables are measured as of the nearest available date prior to the beginning of the accounting year and they are: in column 1 top1, proportion of equity held by largest shareholder, column 2 top5, proportion of equity held by largest 5 shareholders, column 3 top 10 proportion of equity held by largest 10 shareholders, column 4 block5, the proportion of shares held in blocks larger than 5%, column 5 and 6 block5inst and block5ind, the the proportion of shares held in blocks larger than 5% by institutions and by individuals respectively.

Table 2.4: OLS regressions: correlation between ownership concentration and size

	(1) top1	(2) top5	(3) top10	(4) block5	(5) block5inst	(6) block5ind
log employment	-0.0214	-0.0615	-0.0783	-0.0785	-0.0205	-0.051
	(0.0035)	*(0.0045)*	*(0.0044)*	*(0.0054)*	*(0.0035)*	*(0.0051)*
R-squared	0.08	0.31	0.43	0.33	0.11	0.21

Notes: The sample is an unbalanced panel of 268 firms from 1985 to 1997 with 2,395 observations. All regressions are estimated by OLS and include a set of time dummies. Asymptotic standard errors robust to heteroscedasticity and autocorrelation of arbitrary form are reported in italics. The dependent variables are: in column 1 top1, proportion of equity held by largest shareholder, column 2 top5, proportion of equity held by largest 5 shareholders, column 3 top 10 proportion of equity held by largest 10 shareholders, column 4 block5, the proportion of shares held in blocks larger than 5%, column 5 and 6 block5inst and block5ind, the the proportion of shares held in blocks larger than 5% by institutions and by individuals respectively.

wants to explore the relationship between ownership concentration and productivity. If this heterogeneity does not only consist of differences in economies of scale but includes underlying differences in technological efficiencies, managerial and organizational structures, then, controlling for size and allowing for non constant returns to scale does not fully account for this issue.[24]

I try to control for unobserved heterogeneity between large and small firms, by controlling for fixed effects and allowing an autoregressive component in the error term.[25]

Table 2.5 reports estimates of equation 2.6 using the first-differenced GMM estimator and log real value added as dependent variable,[26] imposing constant returns to scale. To analyse the impact of ownership structure on total factor productivity, I include different measures of ownership concentration.

All columns of table 2.5 show that ownership concentration has a positive and significant effect on productivity: the long-run coefficients are remarkably similar across all columns, and range from 0.144, when measuring concentration using the Herfindahl index of concentration to 0.177 for top5 as shown by the coefficient estimated when imposing the Common Factor Restriction. The p-values of the first and second autocorrelation tests (m1 and m2) show no second order serial correlation and the Sargan test confirms that all instruments are accepted. The COMFAC test for common factor restriction shows that the restriction is not rejected by the data.

What do these result mean in quantitative terms? Let us concentrate on only two measures of concentration for sake of brevity: top5 and block5. As shown in table A.5 in the median firm in the sample, the largest five shareholders own 32.77% of outstanding equity. If they increased to the concentration level of the firms at the 75^{th} percentile of the distribution, i.e. to 49.23, they would *ceteris paribus* experience a 2.9%[27] increase in productivity, given our coefficient estimates. Similar

[24]Unreported results show that the bottom panel of table 2.3 remains virtually unchanged when including log employment as additional regressor.

[25]this controls for unobserved characteristics persistent over time but are not fixed, such as managerial ability.

[26]As a robustness checks I report results when the dependent variable is log real sales rather than log real value added. To deflate sales and value added I use the producer price index for firms in the manufacturing industries and the retail price index for firms in the service sector. I checked the robustness of the results to this choice by deflating sales and value added using the GDP deflator.

[27]The result is obtained by calculating the difference between 49.23 and 32.77 and multiplying it by the estimated coefficient, i.e. 0.165*0.177.

Table 2.5: Effect of ownership on productivity
(Dependent variable is log real value added per employee)

	(1) top5	(2) top10	(3) block5	(4) Herf
$ln(K/N)_t$	0.134	0.135	0.141	0.127
	(0.094)	*(0.094)*	*(0.093)*	*(0.097)*
$ln(K/N)_{(t-1)}$	-0.017	-0.018	-0.022	-0.006
	(0.070)	*(0.071)*	*(0.070)*	*(0.073)*
Ownership Concentration$_t$	0.184	0.147	0.179	0.185
	(0.054)	*(0.055)*	*(0.042)*	*(0.100)*
Ownership Concentration$_{t-1}$	0.016	0.034	0.028	0.019
	(0.054)	*(0.053)*	*(0.046)*	*(0.094)*
$ln(VA/N)_{(t-1)}$	0.278	0.282	0.274	0.292
	(0.095)	*(0.097)*	*(0.095)*	*(0.097)*
Wald	0.003	0.016	0.000	0.146
m1	0.000	0.000	0.000	0.000
m2	0.178	0.175	0.147	0.185
Sargan	92.08	92.62	91.567	91.530
df	84	84	84	84
p-Sargan	0.256	0.244	0.268	0.269
$ln(K/N)$	0.151	0.144	0.173	0.155
	(0.089)	*(0.089)*	*(0.087)*	*(0.090)*
Ownership Concentration	0.177	0.149	0.168	0.144
	(0.051)	*(0.052)*	*(0.041)*	*(0.078)*
ρ	0.294	0.342	0.294	0.310
	(0.085)	*(0.080)*	*(0.086)*	*(0.084)*
Comfac	0.341	0.362	0.189	0.571

Notes: The sample is an unbalanced panel of 268 firms.The observations used are 1,591 from 1988 to 1997. All regressions are estimated using DPD98 and include a set of time dummies. Asymptotic standard errors robust to heteroscedasticity and autocorrelation of arbitrary form are reported in italics. Coefficients and robust standard errors are computed from the first-step estimates.
All Columns are estimated by first-differenced GMM estimator. The instruments used for the differenced equation are: va_{t-2}, va_{t-3}, va_{t-4}; k_{t-2}, k_{t-3}, k_{t-4}; n_{t-2}, n_{t-3}, n_{t-4} and Own_{t-1},Own_{t-2}. M1 and M2 report p-values of tests for first order and second order serial correlation in the differenced residuals that are distributed as N(0,1) under the null of no serial correlation. The Sargan test of overidentifying restrictions, computed from two-step estimates, is asymptotically distributed as a χ^2 under the null of instruments validity. degrees of freedom and p-values are also reported.
The second set of estimates are obtained using minimum distance estimators imposing common factor restrictions, that are tested using a χ^2 test, whose p-value is reported as Comfac.
Ownership concentration is measured: in Column 1 by the percentage of equity shares held by the largest 5 shareholders; in column 2 by the percentage of equity shares held by the largest 10 shareholders; in column 3 by the percentage of shares held blockholdings greater or equal to 5%; in column 4 by the Herfindahl index of concentration (the construction of this measure is described in more detail in appendix A.1.2.

calculations for block5 show that moving from the median to the 75^{th} percentile leads to an increase in productivity of 3.7%. These effects seem therefore quantitatively important.

The second question I aim to answer is whether the identity of the owner plays an additional role for productivity. Table 2.6 reports the results. Columns 1 and 2 show that the proportion of shares held by institutions among the largest five shareholders has an additional positive effect on productivity conditional on ownership concentration (measured in column 1 as top5 and in column 2 as block5): the long-term coefficients on this variables are positive and significant. This result is confirmed in columns 3 and 4, where to measure the additional effect of a strong presence of financial institutions, I look at institutional holdings in blocks larger than 5%: in both columns the estimated coefficients are positive, even if the coefficient is only significant at the 15% level in column 4.

The fact that the presence of controlling institutions increases productivity confirm is in line with previous work of Nickell et al. (1997) and of Leech and Leahy (1991), but seems at odds with past evidence on British corporate governance of passive monitoring by institutions (Lai and Sudarsanam, 1998, Faccio and Lasfer, 2000). However, the beneficial impact on firm performance of institutional investors compares favorably to evidence from the US (Carleton et al., 1998, del Guercio and Hawkins, 1999).

2.6.1 Robustness checks

Table 2.7 reports robustness checks. In table 2.5 I assumed weak exogeneity of the ownership variables and I did not control for possible measurement error. In column 1 I report the estimates obtained in column 1 of table 2.5 for reference. Column 2 of table 2.7 shows that the result is robust to the presence of measurement error. Moreover, the point estimate of the top5 coefficient is not significantly different from the one estimated without controlling for measurement error and the differenced Sargan test, reported at the bottom of the column, cannot reject the assumption that there is no serially uncorrelated measurement error in the ownership variable.[28]

[28] I can test the presence of measurement error using differenced Sargan test. The moment conditions are overidentifying restrictions and the set of moment conditions under weaker assumptions is a strict subset of the set of moment conditions under stronger assumptions (see Bond, 2002).

Table 2.6: The role of shareholders' identity on productivity
(Dependent variable is log real value added per employee)

	(1)	(2)	(3)	(4)
	top5inst		block5inst	
	top5	block5	top5	block5
$ln(K/N)_t$	0.138	0.146	0.138	0.143
	(0.094)	*(0.093)*	*(0.094)*	*(0.094)*
$ln(K/N)_{(t-1)}$	-0.015	-0.020	-0.014	-0.019
	(0.070)	*(0.069)*	*(0.070)*	*(0.070)*
Ownership Concentration$_t$	0.217	0.198	0.148	0.153
	(0.054)	*(0.042)*	*(0.055)*	*(0.047)*
Ownership Concentration$_{t-1}$	0.018	0.025	-0.007	0.006
	(0.058)	*(0.049)*	*(0.054)*	*(0.049)*
Institutions as large owners$_t$	0.049	0.045	0.126	0.083
	(0.024)	*(0.025)*	*(0.050)*	*(0.053)*
Institutions as large owners$_{t-1}$	0.002	0.001	0.068	0.061
	(0.028)	*(0.029)*	*(0.056)*	*(0.058)*
$ln(VA/N)_{(t-1)}$	0.277	0.275	0.277	0.275
	(0.095)	*(0.094)*	*(0.095)*	*(0.095)*
m1	0.000	0.000	0.000	0.000
m2	0.203	0.165	0.198	0.164
Sargan	91.554	90.967	92.55	92.05
df	84	84	84	84
p-Sargan	0.269	0.283	0.245	0.257
$ln(K/N)$	0.153	0.175	0.158	0.171
	(0.089)	*(0.087)*	*(0.090)*	*(0.088)*
Ownership Concentration	0.208	0.189	0.134	0.139
	(0.051)	*(0.041)*	*(0.052)*	*(0.046)*
Institutions as large owners	0.047	0.050	0.112	0.076
	(0.024)	*(0.025)*	*(0.050)*	*(0.053)*
ρ	0.293	0.289	0.335	0.328
	(0.084)	*(0.084)*	*(0.080)*	*(0.081)*
Comfac	0.470	0.337	0.226	0.19

Notes: The sample is an unbalanced panel of 268 firms. The observations used are 1,591 from 1988 to 1997. All regressions are estimated using DPD98 and include a set of time dummies. Asymptotic standard errors robust to heteroscedasticity and autocorrelation of arbitrary form are reported in italics. Coefficients and robust standard errors are computed from the first-step estimates. All Columns are estimated by first-differenced GMM estimator. The instruments used for the differenced equation are: va_{t-2}, va_{t-3}, va_{t-4}; k_{t-2}, k_{t-3}, k_{t-4}; n_{t-2}, n_{t-3}, n_{t-4} and Own_{t-1},Own_{t-2}. M1 and M2 report p-values of tests for first order and second order serial correlation in the differenced residuals that are distributed as N(0,1) under the null of no serial correlation. The Sargan test of overidentifying restrictions, computed from two-step estimates, is asymptotically distributed as a χ^2 under the null of instruments validity. degrees of freedom and p-values are also reported.
The second set of estimates are obtained using minimum distance estimators imposing common factor restrictions, that are tested using a χ^2 test, whose p-value is reported as Comfac.
Ownership concentration is measured: in Column 1 and column 3 by the percentage of equity shares held by the largest 5 shareholders; in column 2 and column 4 by the percentage of shares held blockholdings greater or equal to 5%. The variable 'Institutions as large owners' is measured in column 1 and 2 by the proportion of equity held by the largest 5 shareholders in the hand of financial institutions; in column 3 and 4 by the percentage of shares held by financial institutions in blockholdings greater or equal to 5%.

Column 3 reports System GMM estimates. As discussed in section 2.5 these are more efficient conditional on the validity of the additional instruments for the equations in levels. In our sample finding valid additional instruments has proven extremely difficult. I finally used the lagged second difference of value added as additional. Both Sargan and difference-Sargan tests do not reject the validity of the additional instrument. Reassuringly, the long term point estimate is not significantly different than the one in column 1 (estimated using differenced-GMM).

In column 4 I further check the robustness of our results to the adoption of different specifications of the baseline production function: following Nickell (1996), I estimate a dynamic production function that includes as a right-hand side variable the lag of output.

$$y_{it} = \alpha_0 + \rho y_{i(t-1)} + \alpha(1-\rho)l_{it} + \beta(1-\rho)k_{it} + \gamma Own_{it} + \delta_t + \eta_i + v_{it} + m_{it} \quad (2.8)$$

where I include the lagged dependent variable as regressor to account for adjustment lags in the production functions. The estimated coefficient on our preferred measure of ownership concentration is still a positive and significant 0.193.

Column 5 includes 19 industry dummies[29] to take into account industry specific shocks. Firms in different industries might be affected by different shocks because of technological opportunities, specific demand shocks, competition and industrial relation practices.[30] The estimated coefficient does not significantly differ from that reported in column 1.

Finally, in unreported analysis I have also checked for the robustness of my results to the use of real sales as alternative measure of output and to the use of the GDP deflator to deflate value added; the results are robust to both checks.

Thus, I can test the validity of the additional moment conditions under the stronger assumption of endogeneity due to measurement error using differenced Sargan tests. I construct the differenced Sargan test, as the difference between the Sargan value under weak exogeneity and the Sargan value under endogeneity. Under the null, the statistic is distributed as a χ^2 with degrees of freedom the difference between the degrees of freedom of the two Sargan tests. However, as a caveat, I notice that the Sargan test might not detect the presence of measurement error because of the insignificance of the coefficient on the lagged ownership variable.

[29] I assign each of the firm to the sample to the industry in which it has the largest amount of sales. However, one must consider that most of our firms are large conglomerates operating in more than one sector at the same time.

[30] In unreported results, I try to control for industry effects both by including year industry interaction dummies and dividing those firms whose main industry is manufacturing from those in the service sector: the coefficient on ownership concentration is still positive and significant.

Table 2.7: Robustness checks

	(1) *top5*	(2) *Meas. Error*	(3) *System*	(4) *Nickell*	(5) *Industry*
$ln(K/N)_t$	0.134	0.152	0.188	0.120	0.161
	(0.094)	*(0.085)*	*(0.080)*	*(0.074)*	*(0.088)*
$(ln(K/N)_{(t-1)}$	-0.017	-0.042	-0.033		-0.012
	(0.070)	*(0.060)*	*(0.078)*		*(0.072)*
$top5_t$	0.184	0.394	0.162	0.193	0.182
	(0.054)	*(0.195)*	*(0.061)*	*(0.056)*	*(0.055)*
$top5_{t-1}$	0.016	0.063	0.003		0.021
	(0.054)	*(0.125)*	*(0.059)*		*(0.053)*
$ln(VA/N)_{(t-1)}$	0.278	0.246	0.477	0.275	0.296
	(0.095)	*(0.094)*	*(0.095)*	*(0.090)*	*(0.089)*
Wald	0.003	0.049	0.028		0.003
m1	0.000	0.000	0.000	0.000	0.000
m2	0.178	0.144	0.375	0.200	0.198
Sargan	92.08	109.044	106.916	92.886	92.047
df	84	101	94	85	84
p-Sargan	0.256	0.275	0.171	0.262	0.257
$ln(K/N)$	0.151	0.155	0.214		0.183
	(0.089)	*(0.083)*	*(0.072)*		*(0.084)*
$top5$	0.177	0.384	0.142		0.176
	(0.051)	*(0.192)*	*(0.054)*		*(0.052)*
ρ	0.294	0.286	0.532		0.333
	(0.085)	*(0.087)*	*(0.080)*		*(0.077)*
Comfac	0.341	0.416	0.154		0.246
Dif Sargan		16.967	14.030		
df		17	9		
p-Dif Sargan		0.457	0.138		

Notes time dummies are included in all models. Asymptotic robust standard errors are reported in italics. Coefficients and robust standard errors are computed from the first-step estimates. Column 1 replicates estimates as in column 1 of table 2.5. Column 2 reports estimates of equation 2.6 controlling for measurement error. Instrument used in column 2 are va_{t-2}, va_{t-3}, va_{t-4}; k_{t-2}, k_{t-3}, k_{t-4}; n_{t-2}, n_{t-3}, n_{t-4} and $Owne_{t-3}$,Own_{t-4}. Column 3 estimates equation 2.6 using system GMM. Instrument used are for the equations in differences va_{t-2}, va_{t-3}, va_{t-4}; k_{t-2}, k_{t-3}, k_{t-4}; n_{t-2}, n_{t-3}, n_{t-4} and Own_{t-1},Own_{t-2}; for the level equations $\Delta(\Delta va_{t-1})$. Column 4 reports estimates of equation 2.8. Column 5 includes 19 industry dummies. Column 6 is estimated on a sample of 134 firms (709 observations) with below the median number of total employees, taking as the median the size reported for the firm in the first year that it is present in the sample; column 7 is estimated on a sample of 134 large firms, 882 observations.

M1 and M2 report p-values of tests for first order and second order serial correlation in the differenced residuals that are distributed as N(0,1) under the null of no serial correlation. The Sargan and Difference Sargan tests of overidentifying restrictions, computed from two-step estimates, are asymptotically distributed as a χ^2 under the null of instruments validity. degrees of freedom and p-values are also reported.

The second set of estimates are obtained using minimum distance estimators imposing common factor restrictions, that are tested using a χ^2 test, whose p-value is reported as Comfac.

2.7 Conclusions

The chapter aimed to answer the question: does the separation of ownership and control have a negative effect on productivity, as predicted by by principal-agents models?

To answer this question, I used an unbalanced panel of UK listed firms with detailed information on beneficial ownership. This is unique data that contain very detailed time series information for a cross section of listed companies on the concentration and the identity of the firms' owners.

Previous literature has analysed the relationship between ownership and firm market value (for example Demsetz and Lehn, 1985, and Morck et al., 1988) and ownership and productivity growth (Nickell et al., 1997, and Curcio, 1994). This is the first study that relates shareholdings' structure and firm efficiency, certainly for the UK and to my knowledge, in the literature.

The results show that OLS estimates, that do not control for unobserved heterogeneity among firms, are likely to find a negative or insignificant effect of ownership concentration on productivity. After controlling for unobserved firm fixed effects and the endogeneity of the inputs using GMM estimation, concentrated ownership has a positive effect on productivity as predicted by principal agent models. Moreover, I find that the presence of financial institutions as large blockholders has an additional positive effect on productivity, conditional on concentration. Finally, I show that these findings are robust to alternative specifications of the production function and to the presence of measurement error in the ownership variable.

These results contribute to the policy debate on the efficiency of financial institutions as shareholders. It seems particularly relevant for Europe, where the scope for private insurance and non-state pension funds is becoming more and more pressing, but might be policy relevant in less developed countries where privatisation and the development of a full size stock market is still taking place.

Chapter 3

Multinationals and US productivity leadership

3.1 Introduction

International comparisons show that the US is the world's most productive economy[1] and much research has gone into understanding the determinants of this productivity leadership. There are two broad categories of factors that could be responsible for this success: on the one hand the *business environment* and on the other *firm or plant specific* factors. The business environment comprises the quality of a country's workforce, the efficiency of public infrastructure as well as geographical advantages. Firm and plant specific factors include more efficient production processes and management techniques, better marketing or more valuable patents or brands. Plant level studies of business units located in the same country but owned by firms of different nationalities can potentially distinguish between these two hypotheses. Since the business environment is the same for all plants in the sample, any observed productivity differences are due to differences in plant or firm specific factors.

When examining foreign ownership effects such as the suggested US advantage in plant level datasets we have to be careful in choosing our comparison group. For various countries – including the US – researchers[2] have found that foreign owned

[1] see for example O'Mahony and de Boer (2002)

[2] For the UK Griffith (1999), Griffith and Simpson (2001), Oulton (2000) and Harris (1999) using the ARD; Conyon et al. (2002) using firm level data; Davies and Lyons (1991) using industry level data. Doms and Jensen's study 1998 for the US. Lipsey and Sjoholm's study 2002 documents

firms are on average more productive than domestic ones. However, since foreign owned plants are by definition part of a multinational enterprise (MNE) whereas only a small fraction of domestic firms are multinational, this might reflect a general MNE advantage rather than country specific advantages. Several theoretical studies starting with Dunning (1981),[3] have explained from where such an MNE advantage might derive: setting up abroad is likely to be more expensive than setting up at home. Factors such as language barriers and ignorance of local business networks give foreign firms a disadvantage. If they nevertheless manage to stay in business, they must have superior firm specific assets – such as better management techniques and better production technology – that they can share with their affiliates.

Therefore, in order to compare like with like we need to compare US MNEs with other – domestic and foreign – MNEs. While foreign ownership identifiers are commonly included in plant level productivity datasets, data that would allow the identification of domestic MNEs has been scarce. Doms and Jensen (1998) is the first US study that controls for the multinationality of domestic firms. They find that, among multinationals, plants owned by US MNEs are the productivity leaders in the US, whereas domestic non MNE plants lag far behind MNEs owned units.

Using a newly available dataset – the Annual Inquiry into Foreign Direct Investment (AFDI) – we are, for the first time, able to identify domestic MNEs in a large scale UK plant level productivity dataset. This allows us to make several contributions to the existing literature. Firstly, our study qualifies the findings of Doms and Jensen in one important respect: in their study they cannot rule out that the leadership of US MNE owned plants is the consequence of a home advantage rather than of intrinsic transferable firm level advantages. The first innovation of this chapter, therefore, is to establish the leadership of US MNEs in Britain, which shows that the US MNE advantage found by Doms and Jensen is not a home advantage. Secondly, we confirm with British data that the foreign ownership advantage is indeed by and large an MNE advantage. Finally, we attempt to explain the nature of the US and MNE advantage further using the longitudinal dimension of our data.

We examine two questions. Firstly, are the drivers of the MNE and the US advantage firm or plant specific? This distinction is important because the Dunning

higher wages paid by foreign-owned firms in Indonesia.

[3]For a summary of Dunning's argument see Markusen (1995).

account, and many theories involving MNEs (see for example Markusen (1995) and Helpman (1984)), assume a firm specific advantage that multinational enterprises can share among plants. An alternative explanation is that the MNE productivity advantage is driven by an ability of MNEs to takeover plants which themselves have superior productivity even before the takeover. We find that the MNE advantage consists of both firm and plant effects. On the other hand, the additional US advantage seems to be primarily driven by plant effects. US MNEs take over plants that are about 10 percent more productive than plants taken over by other MNEs.

Secondly, we also examine if there is evidence for a causal relationship from foreign engagement of a firm to the productivity of its plants in the home market.[4] This would be in line with theories about technology sourcing or other learning effects(Branstetter 2001 and for a review Keller 2004). To identify such effects we look at UK firms that start investing abroad – i.e. become multinational – during our sample period. However, we do not find any significant evidence for such an effect.

The rest of the chapter is organised as follows: in sections 3.2 and 3.3 we describe our dataset. Section 3.4 shows that US owned plants are the productivity leaders in the UK, both in terms of labour productivity and in terms of total factor productivity (TFP), and that only part of the US ownership advantage can be explained by a multinational effect. In section 3.5 we show that this result is robust to alternative classifications of the foreign group and to different specification of the production function. In particular, we show the robustness of our results when we control for the endogeneity of inputs and accounts for imperfect competition using an approach on the lines of Olley and Pakes (1996) and Levinsohn and Petrin (2000). In section 3.6 we disentangle the US productivity effect using a two-step estimation procedure. Section 3.7 concludes.

[4]Dunning's theory would suggest a causal relation from superior productivity to foreign direct investment.

3.2 Data Sources

Our sample is drawn from the Annual Respondents Database (ARD)[5] which is the UK equivalent of the US Longitudinal Respondents Database (LRD). It is a dataset made available by the Office for National Statistics (ONS) based on information from the mandatory annual survey of UK businesses, called Annual Business Inquiry (ABI).[6] The ARD's unit of observation is defined by the ONS as an 'autonomous business unit'. We refer to this level of observation as a 'plant'.[7] It is important to note that the ARD does not consist of the complete population of all UK businesses. All businesses with more than 100 employees[8] are sampled, but smaller businesses are sampled randomly. Only data on British plants – i.e. excluding Northern Ireland – was made available to us. Each year the sampled plants account for around 90% of total UK manufacturing employment.[9] Our sample is an unbalanced panel of about 19,000 manufacturing plants which we observe annually for the years from 1996 to 2000.

The country of ownership of a foreign firm operating in the UK – and thus the ability to identify foreign owned MNE plants in the UK – is provided in the ARD.[10] While this identifies foreign owned plants, until now it has not been possible to identify UK MNEs. To do this we use the Annual Foreign Direct Investment (AFDI) register.

The AFDI is an annual survey of businesses which requests a detailed breakdown of the financial flows between UK firms and their overseas parents or subsidiaries. The AFDI is thus a survey run at the firm and not at the plant level. The AFDI

[5]More extensive descriptions of the ARD can be found in Criscuolo, Haskel and Martin 2003, Griffith (1999) and Oulton (1997)

[6]Annual Census of Production until 1998.

[7]Some of these business units are spread across several sites and are therefore not plants in the strict sense of the word. In about 80 percent of all cases a business unit is located entirely at a single mailing address.

[8]In some years the threshold was 250 employees, for details we refer to Criscuolo, Haskel and Martin, 2003.

[9]To examine if our results are sensitive to the oversampling of larger plants we run regressions with inverse sampling probabilities as weights. These results, unreported for brevity, are not qualitatively different from the unweighted results reported in the next section.

[10]The ARD data is supplemented here with information from Dun&Bradstreet global "Who own's Whom" database. According to Dun&Bradstreet, the nationality of a plant is determined by the country of residence of the global ultimate parent, i.e. the topmost company of a world-wide hierarchical relationship identified bottom-to-top using any company which owns more than 50% of the control (voting stock, ownership shares) of another business entity.

register provides the sampling frame of the AFDI and contains the population of all UK firms which are engaging in or receiving foreign direct investment (FDI). The working definition of FDI for this purpose is that the investment must give the investing firm a 'significant' amount of control over the recipient firm. The ONS considers this to be the case if the investment gives the investor a share of at least 10 percent of the recipient firm's capital. To conduct the AFDI, the ONS maintains a register which holds information on the country of ownership of each firm and on which UK firms have foreign subsidiaries or branches.[11] This register is designed to capture the universe of firms that are involved in foreign direct investment abroad and in the UK. We consequently define as 'multinational' each plant in the ARD that is owned by a firm which appears in the AFDI register.[12] A problem with the AFDI register is that information is not always up-to-date. If a firm engages or receives FDI, it will only be included in the AFDI register after the ONS learns from various sources, including commercial data and newspapers, that this has happened. Consequently, the register population has varied spuriously over the years with the ONS' success in identifying such firms.

However, we believe that this problem does not weaken the conclusions that can be drawn from our results. If some of the plants which we record as non-multinational are actually multinational plants and we still find that multinationals are more productive than non-multinational plants then this means that this result would be even stronger if we measured the status of all plants correctly.

3.3 Descriptive Statistics

Table 3.1 shows the number of multinational plants that we can identify in the population and in the sample and their relevance in terms of employment and value added. Column 1 reports the number of domestic plants with no FDI, (defined as GB

[11]The ONS distinguishes between subsidiaries and branches as follows: a 'subsidiary' is a company where the parent company holds more than 50% of the equity share capital; a 'branch' is a permanent establishment as defined for UK corporation tax and double taxation relief purposes; companies where the investing company holds between 10% and 50% of the equity share capital, i.e. does not have a controlling interest but participates in the management, are defined as 'associates'. The country of ownership is identified using the nationality of the immediate owner, Office for National Statistics (2002) p.120.

[12]Details of the procedure followed to merge the AFDI and the ARD are reported in Criscuolo and Martin (2003).

Table 3.1: Importance of MNE
(Average numbers and shares 1996-2000)

	number of plants		shares		emp share		va share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	pop.	sample	pop.	sample	pop.	sample	wghtd	unwghtd
GB Non MNE	158,868	8,394	0.96	0.75	0.59	0.41	0.44	0.31
GB MNE	3,062	1,427	0.02	0.13	0.21	0.29	0.27	0.32
US	1,172	615	0.01	0.05	0.10	0.14	0.15	0.19
FOR	1,708	825	0.01	0.07	0.11	0.16	0.14	0.18

Notes: Figures reported are annual averages. Population refers to all businesses in the register, sample refers to businesses in the ARD (all large plants plus a sample of smaller plants). Column 5 uses employment information from administrative data for non-surveyed plants. Column 7 and 8 use value added at factor cost. Column 7 weights surveyed observations using employment weights calculated as described in Appendix B.1 to yield statistics representative of the whole population. $GBnonMNE$ denotes domestic plants with no FDI; $GBMNE$ is one for all domestic multinationals; US is one for all plants owned by a US multinational and FOR is one for all plants owned by non US foreign multinationals.

Source: Authors' calculations using matched ARD-AFDI data over the 1996-2000 period.

Non MNEs), British MNEs (GB MNE), US MNEs (US) and non US foreign owned plants (FOR) in the whole population. Column 2 shows the number of plants in each group for the sample of plants surveyed by the ONS to compile the ARD. Columns 3 and 4 translate these numbers into shares. Column 3 shows that 1 percent of all plants in Britain are US owned, almost as much as all other foreign owned plants combined. Indeed, US MNEs represent more than 40 percent of all foreign owned plants in Britain ((615+825)/825). Similar figures hold for the share in employment (column 5) and value added (column 7), where US owned plants represent 47 and 51 percent of FDI, respectively. These figures are consistent with the fact that the most productive companies are also likely to have the highest market share. Also, since US MNEs are on average larger, the relative share of US MNEs in the selected sample is much higher: whereas in the total population US MNEs take a share of about 1 percent, in the sample the same figure rises to 5 percent.

Table 3.2 reports averages and standard deviations for relevant variables. Panel 1 shows the US owned plants' labour productivity lead: averaging over the whole production sector and not controlling for industry we find that plants owned by US firms have an advantage of 26 percent ((46.57 – 36.87)/36.87) over British MNEs and an advantage of 8 percent ((46.57 – 43.10)/43.10) over other foreign MNEs. In terms of gross output per employee (panel 2) the ranking changes: foreign non-US owned plants are the most productive and in general the foreign advantage becomes more dramatic. Panels 3 and 4 suggest that the figures in panel 2 can be partly

Table 3.2: Summary Statistics in the 1996-2000 pooled sample

		GB non MNE	GB MNE	US	FOR
1	VA/Emp	27.96	36.87	46.57	43.10
		(183.47)	(39.30)	(80.79)	(51.43)
2	GO/Emp	76.55	105.35	146.23	156.39
		(207.92)	(132.22)	(232.02)	(283.73)
3	Mat/Emp	50.54	69.78	99.16	114.43
		(85.04)	(85.91)	(163.67)	(221.25)
4	K/Emp	38.23	65.43	85.54	108.92
		(92.78)	(73.07)	(125.61)	(366.37)
5	Employment	142.15	475.02	537.00	445.62
		(264.51)	(954.81)	(1394.88)	(1134.80)
6	AverageWage	17.25	21.35	24.13	23.40
		(7.89)	(10.13)	(8.53)	(8.21)
7	VA/Sales	0.43	0.40	0.38	0.33
		(0.17)	(0.15)	(0.15)	(0.15)

Notes: Figures are unweighted averages over the sample period. Standard deviations in parenthesis. Figures in panels 1 to 4 and 6 are in thousands of pounds. Figures in panel 5 are head counts. The number of observations in all panels is 38,501. *GBnonMNE* denotes domestic plants with no FDI; *GBMNE* is one for all domestic multinationals; *US* is one for all plants owned by a US multinational and *FOR* is one for all plants owned by non US foreign multinationals.

Source: Authors' calculations using matched ARD-AFDI data over the 1996-2000 period.

Table 3.3: Relative productivity of MNE
(estimates of Equation 3.2)

	(1)	(2)	(3)	(4)	(5)
dep. var	$ln\frac{VA}{L}$			$ln\frac{GO}{L}$	
US	0.349	0.144	0.076	0.045	0.044
	(0.018)***	(0.022)***	(0.007)***	(0.008)***	(0.008)***
FOR	0.261	0.055	0.041	0.010	0.009
	(0.016)***	(0.020)***	(0.006)***	(0.008)	(0.008)
MNE		0.261		0.047	0.047
		(0.015)***		(0.006)***	(0.006)***
$ln\frac{K}{L}$			0.071	0.070	0.072
			(0.003)***	(0.003)***	(0.003)***
$ln\frac{M}{L}$			0.626	0.625	0.622
			(0.005)***	(0.005)***	(0.005)***
lnL			-0.010	-0.014	-0.010
			(0.002)***	(0.002)***	(0.002)***
age					0.000
					(0.001)
$age^2/10$					-0.001
					(0.001)
age_{cens}					-0.003
					(0.007)
obs	38501	38501	38501	38501	38501

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for plants in the same firm. In columns 1-3 the dependent variable is log real value added (at factor cost) per employee. In columns 4-6 dependent variable is plant's real gross output per employee. Both value added and gross output are deflated by 4-digit annual output price deflators. Age_{cens} equals one if the plant exists since 1980. All regressions include region and 4-digit industry time interaction dummies. US equals one if a plant is owned by a US multinational, MNE is one for all plants part of MNE firms and FOR is one for all plants owned by non US foreign multinationals. * significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level. *** significantly different from zero at the 1 percent level.

explained by the fact that non US foreign owned plants have much higher material-to-labour and capital-to-labour ratios than all other plants. Panel 5 shows that US plants are on average larger and pay higher wages. This might imply that at least part of the US advantage is the consequence of scale effects[13] and employment of higher skilled workers. Thus, the US advantage might not be due to technological or managerial superiority but simply to different input choices.

3.4 Foreign or Multinational Effect?

The labour productivity advantage of multinationals, US and non US, reported in row 1 of table 3.2 might reflect the fact the MNEs tend to operate in highly produc-

[13]Here we refer to scale effects at the plant level. In our study we cannot control for the scale of the global operations of MNEs, e.g. we do not have information on 'global employment'.

Table 3.4: Robustness checks

	(1) $ln\frac{GO}{L}$	(2) O-P	(3) O-P, const. μ sectors	(4) TFP	(5) obs
MNE	0.047	0.148	0.166	0.054	11826
	(0.006)***	(0.016)***	(0.038)***	(0.004)***	
US	0.044	0.065	0.110	0.033	2589
	(0.008)***	(0.023)***	(0.062)*	(0.006)***	
EUnorth	0.016	-0.031	0.024	-0.002	798
	(0.012)	(0.050)	(0.152)	(0.009)	
EUsouth	0.012	-0.024	-0.094	-0.016	80
	(0.025)	(0.527)	(0.204)	(0.024)	
France	0.011	-0.004	-0.059	0.005	452
	(0.012)	(0.049)	(0.163)	(0.011)	
Germany	-0.020	0.018	0.116	-0.024	523
	(0.010)**	(0.053)	(0.143)	(0.009)**	
Japan	-0.022	-0.011	0.036	-0.033	364
	(0.014)	(0.072)	(0.167)	(0.013)***	
Netherlands	0.027	-0.041	-0.029	-0.021	385
	(0.016)	(0.042)	(0.144)	(0.012)*	
Tax	-0.106	-0.194	-0.083	-0.069	75
	(0.026)***	(0.066)***	(0.099)	(0.022)***	
other	-0.038	-0.093	-0.041	-0.050	136
	(0.026)	(0.052)*	(0.134)	(0.021)**	
otherEurope	0.062	-0.032	-0.004	0.013	338
	(0.028)**	(0.092)	(0.111)	(0.020)	
otherOECD	0.055	-0.016	-0.065	0.019	222
	(0.019)***	(0.079)	(0.165)	(0.016)	
obs	38501	37850	10326	38253	.

Notes: All regressions include a quadratic polynomial in age, age dummy, time and region dummies not reported in the table for brevity. Columns 1 and 4: robust standard errors in parentheses, estimated allowing correlation between unobservables for plants in the same firm. Columns 2 and 3: bootstrapped standard errors in parentheses. MNEs takes value 1 if plant is part of an MNE group. *US* is one if the MNE group is US-owned. Similarly for the other country groups. Details on the country group classifications are in the appendix B.1. In column 1 the dependent variable is log real gross output per employee. Column 1 estimates a Cobb-Douglas production function. Unreported regressors include log capital per employee, log materials per employee, log employment, and time 4-digit industry interaction dummies. Columns 2 and 3 report the second stage estimates using a modified version of Olley and Pakes approach described in section 3.5. Column 3 restricts the sample to plants in sectors where the test of constant markups μ could not be rejected (see appendix B.3). In Column 4 the dependent variable is log real TFP calculated using a factor share method as described in section 3.5.5. * significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level. *** significantly different from zero at the 1 percent level. Column 5 row 1 reports the number of observations for all MNEs in the sample, row 2 reports the number of observations for US MNEs, row 3 to 13 report the number of observations from MNEs in each country group reported in column 1.

tive industries and/or tend to cluster in particular regions with special geographical advantages.

Thus, we start our econometric analysis by controlling for interacted 4-digit industry time fixed effects and regional dummies. The results of this exercise are reported in column 1 of table 3.3, where we regress labour productivity, measured as real value added per employee on 4-digit industry year dummy interactions, 10 regional dummies and two ownership dummies US, which equals 1 when a plant is a subsidiary of a US multinational, and FOR that takes value 1 when a plant is owned by a foreign, non US, corporation.

We find that US and other foreign owned plants are on average 42 percent and 30 percent respectively more productive than British domestic plants.[14] This sizeable advantage is in line with previous results for Great Britain (e.g. Oulton (2000). But, how much of this advantage is due to these plants being part of a multinational enterprise? Column 2 answers this question by including a multinational dummy MNE that is one whenever a plant is owned by a multinational firm. If this multinational is US owned the dummy US will be one as well. Consequently, in column 2 the US coefficient measures the advantage of US MNEs over British MNEs and the FOR coefficient represents the advantage of non US foreign owned subsidiaries over British MNEs.[15] The coefficients' estimates reported in column 2 show that MNEs enjoy a productivity advantage of 30 percent, the US have a significant additional advantage of 15 percent, while non US foreign owned plants enjoy a smaller but significant 5 percent advantage relative to their British counterparts.

Table 3.2 has shown that both US and foreign MNEs have much higher capital intensity than UK firms. This suggests that part of the observed foreign ownership advantage could be driven by this higher capital intensity. To examine this we need to estimate total factor productivity (TFP). The literature has suggested a variety of different approaches to estimating plant level TFP. We start in this section by estimating a Cobb-Douglas production function by OLS. Thus, we assume that output, Q, is produced using the technology

[14]The percentage differences reported in the text are calculated from the coefficients of the dummy variables in Table 3.3 according to the formula diff = $(e^{\beta^{dummy}} - 1)$ e.g. for the US $0.42 = (e^{0.349} - 1)$.

[15]The performance of US MNEs relative to domestic plants can, therefore, be calculated as the sum of the coefficients on MNE and US and the advantage of other foreign-owned plants as the sum of the coefficients on MNE and FOR.

$$q_{it} = \gamma \sum_{z \in Z} \alpha_z x_{zit} + a_{it} \tag{3.1}$$

where q_{it} is the logarithm of output produced at plant i in period t, γ is the returns to scale coefficient, Z is a set of production factors – labour, physical capital and intermediate inputs – α_z are the production function parameters, and a_{it} is TFP. We examine if TFP systematically varies between various types of MNEs and domestic plants by estimating the following equation

$$\begin{aligned} r_{it} - p_{It} - x_{Lit} \quad = \quad & \gamma \textstyle\sum_{z \in Z} \alpha_z (x_{zit} - x_{Lit}) + \frac{\gamma}{x}{}_{Lit} \\ & + \beta_1 US_{J(i,t)} + \beta_2 FOR_{J(i,t)} + \beta_3 MNE_{J(i,t)} \\ & + \theta_{It} + \psi_R + \varepsilon_{it} \end{aligned} \tag{3.2}$$

i.e. we regress deflated revenue, $r_{it} - p_{It}$, per worker, x_{Lit}, on indexes of inputs, dummies referring to ownership[16] and interacted dummies, θ_{It}, controlling for 4 digit sectors time effects and 10 regional dummies ψ_R to control for location effects within Britain. This approach – although standard practice – raises a number of concerns, such as imperfect competition, endogeneity, the lack of plant specific price indices etc. We discuss these issues and their importance for our results in the following section, and argue that the qualitative results do not change relative to the simple regression described in equation 3.2. We therefore start by discussing these results, reported in the last three columns of Table 3.3.

In column 3 – besides capital and material intensity and regional and industry time fixed effects – we only include US and non US foreign ownership dummies and find that US owned plants are significantly the most productive plants in Britain enjoying a strong and significant TFP advantage of almost 8 percent (with a coefficient of 7.6 as shown by row 1 of column 3) and non US foreign owned plants follow with an advantage of 4 percent relative to the reference group of all British plants. This confirms previous results (e.g. Griffith (1999), Oulton (2000) and Harris (1999)).

Column 4 shows that once we include a separate dummy for being part of an MNE, the advantage of non US foreign MNEs drops to an insignificant 1 percent. US plants maintain a significant advantage of 4.5 percent relative to British MNEs, who, in turn, are 4.8 percent more productive than non MNE plants. This result

[16] $US_{J(i,t)}$, for example, would be equal to 1 if plant i is owned in period t by US firm J.

shows that only part of the US productivity advantage is actually a multinational effect.

Finally, column 5 extends the results of the previous column: it accounts for age effects by including a quadratic polynomial in age,[17] to account for possible differences due to the plants' life cycle, learning effects and/or the age of physical assets. The coefficient of US MNE remains virtually unchanged, while the foreign non US advantage relative to GB MNEs is a non significant 1 percent. Finally, MNEs are on average 4.6 percent more productive than British non MNEs.

Our results thus suggest the following. Firstly, controlling for capital intensity, material usage, scale and age effects, US MNEs are the productivity leaders, with British and non-US foreign MNEs having a comparable productivity advantage with respect to British plants that are not part of an MNE. Secondly, much of the US and all of the non US foreign productivity advantage found in previous studies[18] appears to be an MNE effect.

3.5 Are our results robust?

Several issues arise when estimating Equation 3.2. These include our simple grouping of countries into US and all other non UK countries and issues about estimation and interpretation of TFP, such as the perfect competition assumption underlying equation 3.2, the inflexibility of our production technology and endogeneity problems. These are addressed in this section. Our main tool to account for endogeneity is a modified version of the framework suggested by Olley and Pakes (1996), which is new to the literature.

3.5.1 Country grouping

The aggregation of all non-US foreign owned plants in one group might hide considerable heterogeneity. In column 1 of table 3.4, we differentiate the 'non US Foreign'

[17]Since our age variable is left censored in 1980, we include an age censoring dummy. We have tried alternative specifications for the age effect. We also experimented with including age categories and the logarithm of age which leads to the same conclusions as obtained under the current specification.

[18]cited in footnote 2.

group further into various country groups.[19] We see that US MNEs are still the productivity leaders together with Norway, Switzerland and other OECD countries (mainly Canada and Australia), but as a first glance at the following columns shows, only the US leadership is robust to further checks.

3.5.2 Imperfect competition

As pointed out in the previous section, an implicit requirement for the foreign dummies to reflect a purely technological advantage is perfect competition. To examine the implications of removing the perfect competition assumption we find it useful to follow the model originally introduced by Klette and Griliches (1996). Start by simply recalling the definition of deflated revenue, our actual observed dependent variable at the plant level:

$$r_{it} - p_{It} = q_{it} + p_{it} - p_{It} \tag{3.3}$$

i.e. revenue is quantity times prices (all variables in logs), $q_{it} + p_{it}$, since we do not observe prices at the plant level, we deflate nominal sales using (four-digit) sector level price deflators p_{It}. Given that plant level prices are not observed we need some way of controlling for them with variables we actually observe. This can be done by specifying a demand function which links prices to output. A possible specification of the demand function is (see also Melitz 2000):

$$Q_{it} = \left(\frac{P_{it}}{P_{It}}\right)^{-\eta} \Lambda_{it}^{\eta-1} \Theta_{It} \tag{3.4}$$

where subscripts i denote firm and I industry; Λ_{it} is a firm specific demand shock, η is the industry demand elasticity and Θ_{It} is a sectoral shock to demand.[20] Taking logs of Equation 3.4 and inverting gives:

$$p_{it} - p_{It} = \frac{1}{\mu}\lambda_{it} - \frac{1}{\eta}q_{it} + \frac{1}{\eta}\theta_{It} \tag{3.5}$$

where $\mu = \frac{1}{1-\frac{1}{\eta}}$ is the markup of price over marginal cost implied by profit maximizing behaviour and lower case letters denote logarithms.

[19]details of the country groups classification can be found in Appendix B.1.

[20]This demand function can be derived by assuming monopolistic competition à la Dixit-Stiglitz (see Dixit and Stiglitz, 1977) in the product market.

Combining equations 3.5 and 3.1 with 3.3 gives:

$$r_{it} - p_{It} = \frac{\gamma}{\mu} \sum_{z \in Z} \alpha_z x_{zit} + \omega_{it} + \frac{1}{\eta} \theta_{It} \tag{3.6}$$

where $\omega_{it} = \frac{1}{\mu}(a_{it} + \lambda_{it})$. Equation 3.6 is the equivalent of Equation 3.2 under imperfect competition. A number of things are worth pointing out. Firstly, – as stressed by Klette and Griliches (1996) – the interpretation of the estimated coefficients on the various production factors changes: they are now all divided through by the markup coefficient μ. Secondly – and more importantly for our purpose – without plant level price information it is no longer possible to regard TFP, here denoted as ω_{it} as a shift parameter relating solely to technical efficiency.[21] Rather, $\omega_{it} = \frac{1}{\mu}(a_{it} + \lambda_{it})$ is a composite of both technology shocks a_{it}, demand shocks λ_{it} and mark-up μ. In the light of equation 3.6, how do we interpret the MNE, US and FOR dummies? Let us start by assuming that within 4-digit sectors μ is constant. In this case a higher ω_{it} for US and MNE plants reflects better product quality or consumer valuation or higher technical efficiency. However, as some recent papers[22] have pointed out, revenue based measures of TFP (ω_{it}) might vary between plants for reasons other than product quality or consumer valuation and technical efficiency. In particular, variations in market power – i.e. μ not being constant across plants in the same industry– might explain some of the variation. Market power might well be positively related to the composite of technical efficiency and product quality. This would introduce a bias to TFP estimates which is negatively correlated with true TFP.[23] In the worst case – if e.g. market power derives from government regulation and restrictions to entry for example – there might be no systematic relation between market power and biases to TFP estimates.

We have three reasons which suggest that our results are not driven by market power effects. Firstly, while there are surely some sectors of the UK economy in

[21]Melitz (2000) stresses this point.

[22]see for example Foster, Haltiwanger and Syverson 2003, Syverson 2004 and Katayama, Lu and Tybout 2003.

[23]If in equation 3.6 the coefficients on factor inputs vary because of variation in market power across plants(μ_i) but our estimation model uses fixed coefficients $\bar{\mu} \in [\min_i\{\mu_i\}; \max_i\{\mu_i\}]$ and $Cov(\mu, a_{it} + \lambda_{it}) > 0$, then for plants with high $a_{it} + \lambda_{it}$ we attribute too much output variation to production factors. More intuitively, this is the case because our regression model does not control for the fact that for plants with larger μ an increase in factors would depress prices more.

which government regulation rather than competitive pricing determine the market share of different companies[24] it is hard to believe that this is a general phenomenon in the manufacturing sector as a whole. Consequently we expect, that variations in market power are generally driven by variations in product quality or consumer valuation (λ_{it}).[25] Following the argumentation in the last paragraph, the biases from variations market power would then strengthen our main conclusions: if we tend to underestimate TFP of the better plants such as US MNEs but we still find that they are significantly better, then the result would be even more clear-cut if we would correct for these biases. Moreover if regulation favours certain firms then this should in particular lead to advantages for domestic firms rather than MNE firms in general or US firms in particular. Secondly, large variations in market power might be a particular problem when comparing MNEs with non MNEs. Following the argumentation in the last paragraph, the biases from variations market power would then strengthen our main conclusions: If we tend to underestimate TFP of the better plants such as US MNEs but we still find that they are significantly better, then the result would be even more clear-cut if we would correct for these biases.However, this should be less of an issue when comparing (British) MNEs, with other (US and other foreign) MNEs. Thirdly, we have devised a simple test based on over identifying restrictions of the assumption that μ in equation 3.6 is constant.[26] The hypothesis that μ is constant is rejected in a large number of sectors. However, if we re-compute our earlier regressions for the sectors in which a constant μ *cannot* be rejected, i.e. in those sectors in which market power should not affect the estimated ranking, we come to the same qualitative conclusions on the relative position of various groups of MNEs.

[24]Sectors where this might be the case include petroleum and nuclear fuel (SIC 23) and Utilities (SIC 40/41) which we exclude from the analysis.

[25]A positive relationship between market power and consumer valuation is also the finding of Foster et al. (2003) who investigated the issue on one of the few productivity datasets which includes firm level prices.

[26]The details of this test are reported in Appendix B.3

3.5.3 A more flexible production function allowing for imperfect competition

An additional worry might be that a log linear production function is inappropriate. Klette (1999) has proposed a methodology that integrates a flexible production function into an imperfectly competitive setting. The starting point is a homogenous differential production function:

$$Q_{it} = A_{it}\left[f\left(\mathbf{X}_{it}\right)\right]^{\gamma} \tag{3.7}$$

where $\mathbf{X}_{it}$ is a vector of factor inputs and $f(\cdot)$ is a linear homogenous general differentiable function. Using the mean value theorem we can write output relative to the median firm as:

$$\tilde{q}_{it} = \tilde{a}_{it} + \sum_{z=1}^{Z} \alpha_z \tilde{x}_{zit} \tag{3.8}$$

where small letters with a tilde denote log deviations from the median plant ($\mathcal{M}$) in a given year,[27] and the α_z represent the partial derivatives of the log production function evaluated at some point $\bar{\mathbf{X}}_{it}$ in the convex hull spanned by $\mathbf{X}_{it}$ and $\mathbf{X}_{\mathcal{M}t}$, so that

$$\alpha_z = \gamma f_z(\bar{\mathbf{X}}_{it}) \frac{\bar{X}_{zit}}{f(\bar{\mathbf{X}}_{it})} \tag{3.9}$$

where $f_z(\cdot)$ represents the partial derivative of $f(\cdot)$ with respect to production factor z. The first order condition of profit maximization implies that

$$P_{it}\gamma \frac{Q_{it}}{f(\mathbf{X}_{it})} f_z(\mathbf{X}_{it}) = \mu W_{zit} \tag{3.10}$$

i.e. prices are such that the marginal value product is μ times the marginal cost W of each factor. Our demand function implies that

$$\mu = \frac{1}{1-\frac{1}{\eta}}$$

As pointed out by Klette (1999), equation 3.10 can only be expected to hold for production factors which are easily adjustable. We assume that this is the case for

[27] e.g. $\tilde{q}_{it} = lnQ_{it} - lnQ_{\mathcal{M}t}$

intermediates and labour, but not for capital so that we get:

$$\alpha_z = \mu \frac{W_z X_{zit}}{P_{it} Q_{it}} = \mu s_{zit} \tag{3.11}$$

where s_{zit} is the revenue share of factor z and $z \in \{L, M\}$. Further, because of homogeneity of degree γ of the production function we get

$$\alpha_K = \gamma - \alpha_L - \alpha_M \tag{3.12}$$

and therefore in equation 3.8:

$$\tilde{q}_{it} = \tilde{a}_{it} + \mu \tilde{vi}_{it} + \gamma \tilde{k}_{it} + \tilde{a}_{it} \tag{3.13}$$

where

$$\tilde{vi}_{it} = \sum_{z \neq K} \bar{s}_{jt}(\tilde{x}_{zit} - \tilde{k}_{it}) \tag{3.14}$$

is an index of all variable factors. These results allow us to rewrite 3.6 as[28]

$$\tilde{r}_{it} - \tilde{vi}_{it} = \frac{\gamma}{\mu}\tilde{k}_{it} + \tilde{\omega}_{it} \tag{3.15}$$

The variable factor index $\tilde{vi}_{it}$ can be directly observed from the data, since all that is required are variables for factor inputs and revenue shares of the factors.[29]

3.5.4 Accounting for endogeneity

Equation 3.15 suggests that the final element required to derive an estimate for $\tilde{\omega}_{it}$ is to find an estimate of $\beta_K = \frac{\gamma}{\mu}$, the ratio between the scale and the markup coefficient. Since plant level capital stocks – like all other inputs – are presumably highly correlated with $\tilde{\omega}_{it}$ this is not a trivial undertaking.[30] We address this problem

[28] All aggregate expressions such as p_{It} and θ_{It} in 3.6 disappear because the equation is now written in terms of deviations from the median plant in the sector.

[29] Equation 3.9 suggests that we should evaluate the derivatives – and thus the factor shares – at 'some point in the convex hull'. Since we do not know the exact location of this point and of course we do not know the functional form of the derivative, we follow common practice and approximate by averaging over the factor share at plant i and the factor share at the median plant $\mathcal{M}$ to calculate the shares in vi_{it}; i.e. $\bar{s}_{it} = \frac{s_{\mathcal{M}t} + s_{it}}{2}$. See also Baily et al. (1992) on this.

[30] see Griliches and Mairesse (1995) for a summary on the endogeneity problem and potential solutions.

using a modified version of the approach of Olley and Pakes (1996). Following them we assume that $\tilde{\omega}_{it}$ evolves as a first order Markov Process:

$$\tilde{\omega}_{it} = E\{\tilde{\omega}_{it}|\tilde{\omega}_{it-1}\} + \tilde{\nu}_{it} \tag{3.16}$$

We also assume that capital is only correlated with the expected component of $\tilde{\omega}_{it}$ but not with $\tilde{\nu}_{it}$.[31] Then we can estimate equation 3.15 if we find a control for $E\{\tilde{\omega}_{it}|\tilde{\omega}_{it-1}\}$. In section B.2 we show that conditional on capital and assuming that markups μ are constant across firms in a narrowly defined sector (four digit) there is a monotone relationship between profits – defined as revenue minus variable costs – and $\tilde{\omega}$. Consequently we can invert the profit function and write

$$\tilde{\omega}_{it} = \phi_{\omega}\left(\tilde{k}_{it}, \tilde{\Pi}_{it}\right) \tag{3.17}$$

We do not know what functional form $E\{\tilde{\omega}_{it}|\cdot\}$ takes, but in equation 3.17 we have found a way to express it in terms of observables so that we can rewrite 3.15 as

$$\tilde{r}_{it} - \tilde{vi}_{it} = \frac{\gamma}{\mu}\tilde{k}_{it} + g(\tilde{k}_{it-1}, \tilde{\Pi}_{it-1}) + \tilde{\nu}_{it} \tag{3.18}$$

where $g(\cdot) = E\{\tilde{\omega}_{it}|\phi(\cdot)\}$ is a function of unknown form. To estimate 3.18 we can either employ a semi-parametric procedure or approximate $g(\cdot)$ by a third order polynomial which, for simplicity, is our strategy. An estimator for $\tilde{\omega}_{it}$ can then be obtained as

$$\hat{\tilde{\omega}}_{it} = \tilde{r}_{it} - \tilde{vi}_{it} - \widehat{\left(\frac{\gamma}{\mu}\right)}\tilde{k}_{it} \tag{3.19}$$

Compared to Olley and Pakes (1996) the main innovation of our approach is to use profits and not investment as predictor for $\tilde{\omega}_{it}$. This has a number of advantages. First, a major criticism of the Olley and Pakes framework is that investment might be a very poor predictor of the fixed component of $\tilde{\omega}_{it}$.[32] If firms are essentially in the steady state – and the capital stock in period t reflects the firm's knowledge about $\tilde{\omega}_{it}$ at $t-1$ – then the variation in investment reflects primarily adjustments to news

[31] Olley and Pakes assume that investment in t can only be used for production in $t+1$. We follow a different strategy. We assume that investment is predetermined. Although this would be problematic in the Olley and Pakes methodology, it does not affect our estimation procedure.

[32] see Griliches and Mairesse (1995).

about $\tilde{\omega}$ from period t. Our approach – similarly to Levinsohn and Petrin's 2000 who use material inputs instead of investment – does not suffer from this problem. Plants with high $\tilde{\omega}$ will have higher profits whether or not they are in the steady state. Second, differently from Levinsohn and Petrin, we can identify all relevant parameters from a moment condition on capital without having to assume separability in intermediate inputs or relying on instrumental variable techniques. Also, we do not require any assumptions on the substitutability between variable production factors.[33]

Finally, to examine if measured TFP ($\tilde{\omega}_{it}$) is systematically different between various types of MNEs we run a regression of estimated $\tilde{\omega}_{it}$ on our ownership dummies.

$$\hat{\tilde{\omega}}_{it} = \beta_1 US_{J(i,t)} + \beta_2 FOR_{J(i,t)} + \beta_3 MNE_{J(i,t)} + \tilde{\varepsilon}_{it} \tag{3.20}$$

Column 2 of table 3.4 reports the results of this exercise. We see that controlling for endogeneity and allowing for imperfect competition, non constant returns to scale as well as for a very flexible production technology has no qualitative and only small quantitative implications for our results. Column 3 shows estimates computed with the same method, but including in the second stage regression – equation 3.20 – only those sectors for which our test[34] of constant markups μ could not be rejected. This suggests the same qualitative conclusions as before.

3.5.5 Other approaches to TFP estimation

The simplest way to handle the endogeneity problem in production function estimation is to follow a factor share approach which involves no regression analysis at all. In table 3.4 – for completeness – we also report our results from using such an approach. Following Baily et al. (1992) and adopting a strategy similar to the one used to calculate the variable factor index vi_{it} in the previous subsection[35] we

[33]For a more detailed discussion of our approach see Martin (2003).

[34]as described in Appendix B.3

[35]This approach is equivalent to imposing $\frac{\gamma}{\mu} = 1$ which rules out imperfect competition and nonconstant returns to scale.

calculate TFP as

$$\tilde{\omega}_{it}^{BHC} = \tilde{r}_{it} - \bar{s}_{Mit}\tilde{m}_{it} - \bar{s}_{Lit}\tilde{l}_{it} + (1 - \bar{s}_{Mit} - \bar{s}_{Lit})\tilde{k}_{it} \qquad (3.21)$$

Column 4 shows that even under this specification our main results of a general MNE advantage and a further US advantage prevail. Note, however, that the point estimates found for the MNE and US effects are considerably smaller compared to results in columns 1 and 2. This is a consequence of imposing $\frac{\gamma}{\mu} = 1$ which we implicity do in equation 3.21. If we use the TFP estimation strategy described in the previous sections we typically find $\frac{\gamma}{\mu} < 1$ suggesting the prevalence of imperfect competition. Now if there is a positive correlation between performance and capital input $(Cov(\omega_{it}, k_{it}) > 0)$ then standard TFP assigns too much of the variation in $r_{it} - vi_{it}$ (see equation 3.15) to capital so that better performing plants look worse than they are.[36]

To summarize, the results shown in table 3.3 seem to be robust: US MNEs are the most productive with British MNEs and foreign non US MNEs alternating each other in the second position. British plants that are not part of an MNE are the least productive. In the next section we shed more light on the factors, which drive these differences.[37]

3.6 Explaining the US productivity leadership

In the previous sections we have been able to establish two main results. Firstly, plants owned by MNEs are on average more productive than non MNE plants and secondly, plants owned by US MNEs are more productive than all other MNEs. Using the longitudinal dimension of the current data we try to distinguish between

[36]An alternative method to estimate TFP controlling for the endogeneity of inputs would be Difference GMM (Arellano and Bond (1991)) and System GMM (Blundell and Bond (1998)). We attempted to use these estimation methods on our sample, but we encountered two problems: firstly the time period of our sample is too short, 5 years, with less than 7 percent of the plants observed over the whole time period; secondly, due to the fact that the ARD surveys small plants randomly, only 12 percent of the plants have continuous time series information.

[37]Other unreported robustness checks include weighted regressions and regressions that control for unobserved skill level in the firm. In the latter we include in equation 3.2 plant average wage as a proxy for the average skill level of workers; we cannot further distinguish between average wage for operatives and average wage for administrative employees unlike previous studies (e.g. Griffith and Simpson (2001)) because since 1996 this information has not been reported in the ARD.

Table 3.5: Sources of MNE and US advantage
(Productivity is residual of gross output regression)

	(1) all	(2) change to MNE	(3) currently domestic
MNE	0.007	0.007	0.007
	(0.007)	(0.008)	(0.007)
ever MNE firm	0.066	0.018	
	(0.013)***	(0.012)	
ever MNE plant	0.155		0.160
	(0.025)***		(0.025)***
ever US firm	-0.002	-0.023	
	(0.017)	(0.020)	
ever US plant	0.098	0.120	0.121
	(0.016)***	(0.032)***	(0.024)***
ever other for firm	0.017	0.009	
	(0.014)	(0.019)	
ever other for plant	0.048	0.017	0.035
	(0.015)***	(0.026)	(0.020)*
green dom	-0.007	0.022	0.001
	(0.010)	(0.033)	(0.012)
green mult	0.037		0.081
	(0.016)**		(0.057)
green US	0.006		-0.087
	(0.030)		(0.072)
green other	0.001		-0.010
	(0.024)		(0.072)
obs	38501	2501	25558

Notes: Bootstrapped standard errors in parentheses. Row 1 (**MNE**) reports first-stage estimates of the going global effect. Row 2 and below: coefficients and standard errors are from the second-stage of our estimation procedure. Dependent variable is fixed effects estimated in the first step. **ever MNE firm** equals 1 if the plant belongs at time t to a firm which is MNE. **ever MNE plant** is 1 if the plant has ever been owned by a MNE over the course of the sample period. Similarly for the **ever US** and **ever FOR** dummies. **green** dummies take value one for all plants that are established during the course of the sample period (1996-2000), **green GB non MNE** is one for plants owned by domestic firms when established. **green MNE** is one for plants owned by MNE firms when established. **green US** (**green FOR**) is one for plants owned by US (other foreign) firms when established. Column 1 use the whole sample of 38,501 observations. Column 2 only includes plants that incur a change in status over the period they are present in the sample. Column 3 only keeps observations of non MNE plants and of MNE plants when owned by non MNE firms.
* significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level.
*** significantly different from zero at the 1 percent level.

three hypotheses on the sources of the MNE and US advantages.

A first hypothesis is that plants owned by MNEs might be more productive because multinational firms takeover the best plants in any country. We call this the *plant picking* effect. This might be because multinational corporations have more resources to finance takeover activity or because they are simply better at spotting top performing plants.

A second hypothesis is that multinational firms are characterised by superior shared assets that improve the performance of any plant they takeover.[38] Examples include international distribution networks, special management techniques, patents, blueprints, trade secrets, and reputation effects. We refer to this as the *best firm*

[38]we can think of this effect as the 'ownership specific' factors in Dunning's explanation of FDI or the 'knowledge capital' of the firm in Markusen.

Table 3.6: Status changes in the data
(Transitions in ownership and MNE status in sample 1996-2000)

	(1) GB non MNE	(2) GB MNE	(3) US	(4) FOR
	Status changes			
GB Non MNE	11164	589	225	304
GB MNE	251	3170	101	46
US	155	62	1290	48
FOR	138	42	26	1857
	Status changes with ownership change			
GB Non MNE	1511	255	225	304
GB MNE	164	51	101	46
US	155	62	131	48
FOR	138	42	26	246

Notes: *GB non MNE* denotes domestic plants with no FDI; *GB MNE* is one for all domestic multinationals; *US* is one for all plants owned by a US multinational and *FOR* is one for all plants owned by non US foreign multinationals. The table reports in panel one the number of plants that change their MNE status; in panel two the subset of these that also experienced an ownership change. For example Row 1 Column 2 reports that there are 589 transitions from GB non MNE to GB MNE. Row 5 Column 2 reports that in 255 cases these transitions also involved a takeover. Number of observations in the sample is 38,501. The period considered is 1996-2000.
Source: Authors' calculation using the ARD AFDI matched data.

effect.

Finally, plants owned by firms that start investing abroad might experience productivity improvements as a direct consequence of FDI, because of, for example, firm-level scale economies, cheaper options to hedge against exchange rate risk, technology sourcing from abroad or other learning effects((Branstetter 2001 and Keller 2004)). We call this the *going global* effect.

we represent these hypotheses formally as follows.[39] Productivity, $Prod_{it}$, of plant i at time t can be written as:[40]

$$Prod_{it} = \alpha_i + \zeta_{t,J(i,t)} + \varepsilon_{it} \tag{3.22}$$

where $\zeta_{t,J(i,t)} = \zeta_{J(i,t)} + \beta_{MNE} MNE_{J(i,t)}$; i.e. productivity can be decomposed in an effect $\zeta_{t,J(i,t)}$ due to the parent firm of plant i at time t and a plant specific effect α_i.[41] $\zeta_{t,J(i,t)}$ is then decomposed further in a time invariant firm specific effect $\zeta_{J(i,t)}$ and an effect which allows a causation from becoming multinational to productivity,

[39]For simplicity at this stage we do not separate the MNE group further into separate US and foreign other (FOR). We reintroduce those in the empirical analysis below.

[40]In principle we can decompose any productivity measure in this way. In our actual estimations below we use TFP calculated as the residual from equation 3.2 as reported in column 5 of table 3.3.

[41]For simplicity we abstract from differences between various types of MNEs.

β_{MNE}. In this setting the *best firm* effect can be represented as

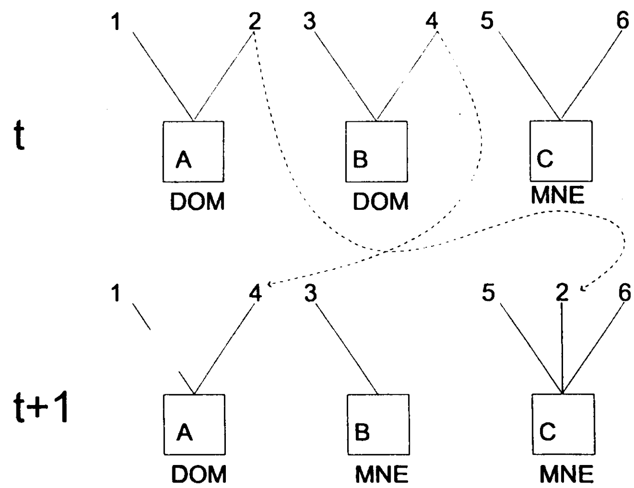
$$E\{\zeta_{J(i,t)}|MNE_J^{ever}=1\} > E\{\zeta_{J(i,t)}|MNE_J^{ever}=0\} \tag{3.23}$$

where MNE_J^{ever} is a time invariant dummy variable that is equal to one if firm J is a multinational, British[42] or foreign, i.e. for MNEs we expect a higher firm fixed effects than for other firms. The *plant picking* effect, on the other hand, can be represented as

$$E\{\alpha_i|MNE_i^{ever}=1\} > E\{\alpha_i|MNE_i^{ever}=0\} \tag{3.24}$$

where MNE_i^{ever} is a dummy that is equal to 1 if plant i is being owned at some point in the sample by a multinational firm in the periods when this firm is actually investing abroad.[43] Finally, the *going global* effect, is represented as $\beta_{MNE} > 0$. To explain how we identify these various effects from our data we introduce an example in figure 3.1.

Figure 3.1: An example



Suppose our sample consists of 6 plants[44] which are owned by 3 different firms (A, B and C). We observe them for two periods, t and $t+1$. In period t firms A and B are domestic, whereas firm C is an MNE. In period 2 firm B starts investing

[42]Note that, for a given firm, MNE_J^{ever} is time invariant characteristic. So for a UK MNE it would be equal to 1 even in the years where it has not yet started investing abroad.

[43]This latter qualification is of relevance for British MNEs in periods where they have not yet started investing abroad. Plants which they sell or close down before investing abroad would be classified as non MNE plants owned by an MNE.

[44]numbered 1 to 6 in figure 3.1.

abroad and thus becomes an MNE whereas A stays domestic.[45] Moreover, we have the following takeover events: plant 2 is acquired by C and plant 4 is sold off to firm A by firm B before it starts investing abroad.[46] How can we differentiate between the various MNE effects discussed earlier with the variation in this example? Consider first the *plant picking* effect. The one plant in the example that was taken over by an MNE is plant 2. If we found that in year t plant 2 had a higher productivity than plant 1 this would be evidence of a *plant picking* effect. To examine the existence of *best firm* effects we can compare the productivity of plant 2 in year $t+1$ relative to year t. If its productivity increases after it is taken over by firm C this would be evidence of *best firm* effect.[47] Finally, for the going global effect we have to look at firm B and examine if the productivity of its plant 3 increases from t to $t+1$.

How do we implement this econometrically? Our estimation strategy proceeds in two steps. In the first step our objective is to obtain a consistent estimate of β_{MNE}. Given the assumptions of our model, the source of endogeneity is the potential correlation between the unobserved effects α_i and ζ_J and the variable of interest $MNE_{J(i,t)}$.[48] Note that if we take deviations of the dependent and explanatory variables from the mean across all observations of a specific firm plant combination, the two fixed effects vanish:

$$\widetilde{x_{it}} = x_{it} - \frac{1}{\#_{it}\left[J(i,t)\right]} \sum_{\tau \text{ s.t.} J(i,\tau)=J(i,t)} x_{i\tau} \tag{3.25}$$

where $\#_{it}\left[\cdot\right]$ is a function that returns the number of periods plant i is owned by the firm $J(i,t)$. This corresponds to the fixed effects transformation where the cross sectional units are not the plants nor the firms but each firm-plant combination in the dataset. Consequently, running a least squares regression on

$$\widetilde{Prod_{it}} = \widetilde{MNE_{J(i,t)}}\beta + \widetilde{\varepsilon}_{it} \tag{3.26}$$

[45]In terms of our earlier dummies we would thus have $MNE_A^{ever} = 0$, $MNE_B^{ever} = 1$ (both, in year t and t+1) and $MNE_C^{ever} = 1$.

[46]Consequently $MNE_1^{ever} = 0$ and $MNE_4^{ever} = 0$ whereas for all other plants $MNE_i^{ever} = 1$ $\forall i = 2, 3, 5, 6$.

[47]Equally, we could look if the productivity of plant 4 decreases once it is taken over by A in period $t+1$.

[48]Note that we are assuming $E(\varepsilon_{it}|MNE_{J(i,t)}, \zeta_{J(i,t)}, \alpha_i) = 0$, i.e., conditional on the fixed effects, changes in MNE status are not correlated with the time varying shocks. We discuss this assumption in more detail later in this section.

will give us a consistent estimate of β_{MNE}. [49] This, in turn, can be used to obtain an estimate of the fixed effects for all firm-plant combinations

$$\widehat{\zeta_{J(i,t)} + \alpha_i} = Prod_{it} - \hat{\beta}_{MNE} MNE_{J(i,t)} \tag{3.27}$$

Our second stage proceeds by running a regression of the predicted fixed effects on the MNE_J^{ever} and MNE_i^{ever} dummies:

$$\widehat{\zeta_{J(i,t)} + \alpha_i} = \beta_J^{ever} MNE_{J(i,t)}^{ever} + \beta_i^{ever} MNE_i^{ever} + v_{it} \tag{3.28}$$

The plant picking effect is in this setting represented as $\beta_i^{ever} > 0$ and the best firm effect as $\beta_J^{ever} > 0$.

Table 3.5 shows results from this regression exercise. Start by considering column 1 where we regress both stages on the complete sample. Note first that, as in section 3.4, we control separately for US MNEs and other foreign effects with dummies that are constructed according to the example of MNE_J^{ever} and MNE_i^{ever}. Moreover, we include a set of dummies that are equal to one if a plant is setup as a greenfield investment during our sample period by either a domestic or an MNE firm.[50] This is to control for a potentially important source of heterogeneity in the data that could bias our estimate of the *best firm* effect: if any MNE's shared assets' effects could only be realised in plants which are setup as greenfields by multinationals then ignoring these greenfield dummies would bias our firm effects downwards. Consider now the results in column 1. Firstly, row 1 reports the coefficient β_{MNE} estimated in the first step. The positive but insignificant coefficient's estimate of 0.007 suggests that there is no strong *going global effect*.[51] Rows 2 and 3 show that the MNE

[49] One crucial assumption required is that the change in MNE status is not correlated with the time varying part of the error term. Thus, we are implicitly assuming that the timing of the MNE status change is exogenous. A scenario where this might be violated is the following: plants could have a higher probability of being taken over in years where they suffer from idiosyncratic large negative shocks. To examine the relevance of this scenario we run probit regressions of the probability of changing status to MNE on time dummies and TFP growth in the previous year. The results show that productivity growth is not significantly correlated with the probability of being taken over by an MNE. Also, since we do not have good instruments for changes in MNE status we thought of controlling for the endogeneity of MNE status changes using GMM methods. However, we cannot use these estimation methods as explained in footnote 36.

[50] The reference category for this set of dummy variables are the plants which were set up before our sample started so that we do not know who set them up.

[51] This first row result is the same in all columns, because the various columns only differ with respect to the second stage regression

advantage seems to be due to both a *plant picking* effect and a *best firm* effect. We find significant coefficients' estimates of 0.066 and 0.155, respectively. Looking at rows 4 and 5 we also have evidence that the additional US advantage is a consequence of *plant picking* rather than a *best firm* effect: plants that are at some point US owned have an average advantage of about 10 percent over all other MNE plants. Row 7 shows a significantly positive foreign non-US plant effect of 4.8 percent, which is lower than the US plant effect.

Finally, rows 8 to 11 report the 'greenfield' effects. Row 9 shows that plants that are setup by MNEs enjoy a 3.7 percent advantage relative to non greenfield domestic plants, significant at the 5 percent level; rows 10 and 11 show that there is no additional advantage from being setup by a US or a foreign MNE.

What could be a potential concern with our estimates in column 1? Note that in terms of the example in figure 3.1 the MNE firm coefficient,β_J^{ever},[52] is calculated as a weighted average of all observations of plants currently owned by an MNE firm minus a weighted average of observations of all plants that are not owned by an MNE.[53]

Thus, β_J^{ever} could be high for two reasons. Firstly, if plants such as 3, 5 and 6 which throughout the sample period are owned by multinationals are very productive or secondly, if plants such as 2 which change their ownership over the course of our sample had a strong increase in productivity after being taken over by an MNE.[54]. To examine which of the two is more relevant is interesting because it gives us an idea of the time span which might be necessary for MNEs to increase the productivity of the acquired plants. Note, that a particular characteristic of plants such as 5 and 6 is that they have been owned by an MNE for longer than plants such as 2.[55] Consequently, in column 2 we restrict our sample for the second stage regression to MNE plants which had a transition from domestic to MNE over the course of our sample.[56] If we still find significant MNE firm effects this is an indication that MNE firms are very quick in improving the productivity of acquired plants. However, in

[52]And by analogy all other firm coefficients in column 1.

[53]i.e. in terms of the example in figure 3.1, the best firm effect is calculated as $WeightedAverage\{2_{t+1}, 3_t, 3_{t+1}, 4_t, 5_t, 5_{t+1}, 6_t, 6_{t+1}\} - WeightedAverage\{1_t, 1_{t+1}, 2_t, 4_{t+1}\}$.

[54]Or if plants such as 4 had a dramatic drop in productivity after being sold off

[55]Since we have a sample period of 5 years and for plants such as 2 we must observe at least one takeover, the longest time such a plant could be owned by an MNE is 4 years.

[56]Like plant 2 in the example.

column 2 the MNE firm dummy reduces to less than a third relative to column 1 – from 0.066 to 0.018 – and is only borderline significant.[57]

Equally, there might be an issue with our estimates of the *plant picking* effects in column 1. The MNE *plant picking* effect – and by analogy the US and other foreign *plant picking* effects – are computed as the weighted average of all observations from MNE^{ever} plants minus a weighted average of all observations from non MNE^{ever} plants.[58]

Therefore, our calculations also include observations from periods in which some of the plants are owned by an MNE^{ever} firm.[59] Thus, the robustness of our plant effects estimator thus depends on our ability to correctly control for any firm effect that the plants are subject to in those periods. An easy way to scrutinize our results is to restrict the second stage regression to the sample of observations in which plants are owned by non MNE firms.[60] This is done in column 3. As in column 1 we find strong MNE and US plant picking effects suggesting that MNEs and especially US MNEs pick the better plants. In contrast to column 1, we cannot find an additional plant picking effect for plants which are taken over by non US foreign firms.

What other potential concerns arise concerning this analysis? A strong assumption in our identification strategy is that all unobserved heterogeneity can be captured by our two fixed effects. There might be important deviations from this model. For example plants might be acquired by MNEs not according to their productivity level but according to their future growth potential. To investigate this in more detail we would require a dataset covering a longer time period than we have at present. Also note that if this issue is important it would lead in our framework to an overestimation of the firm effects, especially in column 2 were we focus on plants that were taken over by MNEs during the sample period.

Another possible source of endogeneity is related to the possibility that the takeover by an MNE is correlated with time varying shocks as well as the plant

[57]In unreported results, we explore this issue in more detail. We find that if we restrict this analysis to plants that we observe for at least two years after takeover, i.e. to 692 observations, the MNE firm dummy coefficient is estimated to be 0.035 with a bootstrapped standard error of 0.022.

[58]Thus, in terms of our example, the plant picking effect is calculated as *Weighted Average* $\{2_t, 2_{t+1}, 3_t, 3_{t+1}, 5_t, 5_{t+1}, 6_t, 6_{t+1}\}$ - *Weighted Average* $\{1_t, 1_{t+1}, 4_t, 4_{t+1}\}$

[59]in terms of the example these are $(2, t+1)$ and $(4, t)$

[60]i.e. identify the plant effect from *Weighted Average* $\{(2, t)\}$ - *Weighted Average* $\{(1, t), (1, t+1), (4, t+1)\}$.

fixed effects. For example, the transition to foreign ownership might not only depend on fixed characteristics of plants but also on temporary negative shocks which make the plant temporarily weak and thus a target of e.g. a hostile foreign takeover. Alternatively, one might think of a case in which the MNE gains interest in a particular plant because of a positive productivity shock. It is therefore not clear in which direction the bias will go.

Apart from our estimation strategy, a general concern might be that our dataset does not have sufficient movement of firms between multinational states and of plants between different types of firms. This is the topic of table 3.6 which reports the occurrence of all these changes in our dataset. The upper panel reports the number of status changes for each possible transition between GB non MNE, GB MNEs, US MNEs and Non US Foreign MNEs (FOR). For example the cell in row 1, column 2 reports that in our sample there are 589 transitions from GB non MNEs to GB MNEs. The lower panel reports only the number of status changes that also involved an ownership change. Therefore, the cell in row 5 column 2 reports that 255 of the 589 British plants that became multinational did so by means of an ownership change, i.e. a takeover. This implies that the remaining 334 plants became part of a British MNE because the firm they belonged to started investing abroad. This is the variation we use to identify β_{MNE}. In total, the upper panel shows that we have 1,118 changes between non MNE and MNE status.[61] The lower panel shows that 784 of these changes involved a change in ownership, i.e. a takeover. Overall panel 1 of table 3.6 shows that about 10 percent of all the transition events we can observe in the data involve a change in multinational status.[62] From panel 2 we can derive that about 40 percent of all ownership changes in our sample involve changes between multinational status.[63] Thus, while the majority of plants do not switch status, in the data there is still some non negligible amount of status changes.

To summarize, our results suggest the following. First, in line with the predictions of Dunning, we find evidence for an MNE firm effect. This evidence is stronger when we consider plants which have been part of an MNE for a longer time period. This suggests that MNE firm specific advantages require some time to materialise

[61]we obtain this figure by summing the off diagonal elements of row 1 and column 1 in the upper panel.

[62]This is computed as the share of all off diagonal elements to the sum of all cells of table 3.6.

[63]Once again computed as the share of all off diagonal elements this time of panel 2

at the plant level. Second, we find strong and robust evidence of plant picking by MNEs. Third, the US seems to be the best at "cherry picking" the most productive plants in Great Britain, and indeed this seems to be the source of the additional US advantage found in the OLS regressions. Fourth, there seems to be a small advantage of foreign non US MNEs firms in acquiring better plants, although this is significantly smaller than for their US counterparts and not robust across different specifications. Fifth, we do not find any evidence that FDI of British firms has a direct short run beneficial effect on the productivity of plants they own in Britain, but again this result might be driven by the rather small length of our sample period.

3.7 Conclusions

International comparisons show that the US is the world's most productive economy. The US productivity leadership found in cross-country studies is mirrored by microevidence when comparing US-owned plants with other foreign owned and domestic plants.

However, when examining foreign ownership effects such as the suggested US advantage in plant level datasets care needs to be taken that one is comparing like with like: we need to compare US MNEs with other – domestic and foreign – MNEs.

Doms and Jensen (1998) is the first US study that controls for the multinationality of domestic firms. They find that, among multinationals, plants owned by US MNEs are the productivity leaders in the US, whereas domestic non MNE plants lag far behind MNEs owned units.

Using a newly available dataset – the Annual Inquiry into Foreign Direct Investment (AFDI) – we are the first to identify domestic MNEs in a large scale UK plant level productivity dataset. This allows us to contribute to the existing literature in three different ways.

Firstly, we can show that the productivity leadership of US owned plants relative to all other multinationals, British and foreign, remains after controlling for industry and observable firm characteristics. Our study, therefore, qualifies the findings of Doms and Jensen in one important respect: in that we can exclude that the leadership of US MNE owned plants is the consequence of a home advantage rather than of intrinsic transferable firm level advantages.

Secondly, we show that, except for the US, the foreign ownership advantage in Britain is indeed by and large an MNE advantage. For non US foreign owned plants, multinationality explains most of the foreign advantage; once we control for their capital intensity they are as productive as domestic MNEs.

Finally, we go further and analyse the sources of two advantages: that of MNEs and that of US owned plant relative to other MNEs. Using the longitudinal dimension of our data, we examine three hypotheses.

First, the literature has suggested that the superior perfomance of MNEs, are driven by specific firm level assets – such as managerial skills, patents, branding and production processes – which MNEs can transfer to any plant they own across the globe (Markusen 1995 and Dunning 1981). Second, MNEs are believed to be better at picking the best plants in the host country. Thirdly, plants owned by British firms that start investing abroad might experience productivity improvements as a direct consequence of FDI, because of, firm-level scale economies, technology sourcing from abroad or other learning effects (see Branstetter (2001) for evidence on technology sourcing between Japan and the US).

We find evidence confirming that the MNE advantage can be attributed to both MNEs having higher firm fixed effects and MNEs owning plants with better plant fixed effects. This suggests that the MNE advantage is driven by both, the sharing of superior firm level assets across plants and the ability to select the better plants in a country. Thus, our results support the idea that MNEs have unobserved superior assets that they can share with their subsidiaries, as outlined by Dunning, Markusen and Caves, but they also suggest that MNEs takeover strategy might be significantly better than other firms.

With regard to the US leadership, we find that the additional superiority of US firms over all other MNEs seems to be entirely driven by a particular ability of US firms to takeover the best British plants rather than improving the productivity of acquired plants any more than other MNEs do.

Finally, our data does not find any robust evidence for an ex-post productivity increase in domestic plants of British firms that start investing abroad. This might be due to the short time series available to us.

Future research might, therefore, focus on the as yet unanswered question: why are US firms better than all other MNEs at obtaining the best plants? There are several possible explanations. One hypothesis is that managers of US MNEs pursue more aggressive takeover strategies and have specific skills that make them more successful in this activity. A second explanation is related to the particular time period considered. Indeed, in the second half of the 1990s, the US Stock market experienced a boom with equity prices registering a spectacular increase. During that period, the S&P500, the Dow Jones Industrial and the Nasdaq Composite indexes more than doubled. US MNEs, overvalued in the US stock market, and thus with access to low cost capital, might have found it more profitable to use this capital to target firms abroad (e.g. in the UK) not affected by the same stock market bubble, rather than in the home country (the 'cheap capital' view of FDI (Baker et al., 2004)).

With the data at hand, we cannot thoroughly investigate these hypotheses, but this is an area of research that deserves further exploration.

Chapter 4

How do Multinationals innovate more?

4.1 Introduction

Why do different firms and countries produce different amounts of new knowledge? This question is central to a number of literatures in economics, most of which approach the question with the "knowledge production function" (KPF) framework. Commonly attributed to Griliches (1979) and to Griliches and Pakes (1980), this framework posits that output of new knowledge depends on investment in discovering new knowledge – e.g. research and development (R&D) activity – and on the flow of ideas from the existing stock of knowledge – i.e. the base upon which to make innovations. Different research areas typically make different use of the KPF.

In the macro-growth literature, the existing stock of knowledge is often assumed to be a public good. For example, Jones (2002) assumes: "Ideas created anywhere in the world are immediately available to be used in any economy. Therefore, the [stock of ideas] used to produce output corresponds to the cumulative stock of ideas created anywhere in the world and is common to all economies." And in much of the theory work, steady-state output growth and levels hinge crucially upon the returns to scale in the KPF to both knowledge investments and flows (see Jones, 2003).[1]

[1]Other examples include Parente and Prescott (1994), in which "World knowledge is meant to represent the stock of general and scientific knowledge in the world (i.e., blueprints, ideas, scientific principles, and so on). We assume that all firms have access to this knowledge. Thus, general and scientific knowledge spills over to the entire world equally."

Much of the industrial organization literature starts from a different point; namely, that knowledge stocks do not flow perfectly and that efforts to innovate depend importantly on the degree of success in learning from these stocks. Important research areas include measuring knowledge output and flows from knowledge stocks, with much work using R&D capital stocks, patents and patent citations. There is also interest in whether knowledge flows across firms via "spillovers" or via market-mediated transactions, and on the impact of new knowledge on productivity in making goods and services.

The international trade literature suggests that globally engaged firms are particularly "knowledge intensive". In recent years a growing body of empirical evidence confirms that firms that are multinational and/or exporters are particularly knowledge intensive.

For example, in the manufacturing sectors of the United States (Doms and Jensen, 1998) and the United Kingdom (see Chapter 3) it is multinational firms – parents and also affiliates of foreign-owned firms – that show the highest levels of total factor productivity (TFP). Similarly, exporters in many countries exhibit high productivity levels and/or growth (see the survey of Tybout, 2000). There is also evidence that multinationals use more knowledge inputs: e.g., multinationals seem to do more advertising (Brainard, 1997), or the evidence in Bernard et al. (2004) that in recent decades the parents of U.S.-based multinationals have consistently performed about two-thirds of all U.S. private-sector research and development (R&D) despite accounting for barely 1/20th of 1% of all firms. Motivated by this body of empirical evidence, the now-standard trade models of multinationals (Markusen, 2002 for an extensive treatment, or Carr et al., 2001 for an abridged summary) make the crucial assumption that these firms are particularly knowledge intensive relative to purely domestic firms. Indeed, in this "knowledge capital" model multinationals arise via foreign direct investment (FDI) largely because of the desire (and ability) to deploy firm-specific knowledge assets in multiple countries despite the co-ordination and set-up costs of multi-plant production with parents predominantly creating knowledge assets, and these assets flowing within firms, mainly from parents to affiliates. There is ample evidence of this cross-border intra-firm knowledge transfer (e.g. Mansfield and Romeo, 1980, and Moran, 2001). There is mixed evidence, at best, whether this knowledge somehow "spills over" from affiliates to domestic firms in host countries (e.g. Aitken and Harrison, 1999 and Haskel et al., 2002).

Although these approaches have a somewhat different emphasis they have all encountered common serious measurement and econometric problems. First, measuring new knowledge is difficult. Some studies use changes in TFP, but this can of course change for other reasons (most notably mismeasurement of real physical inputs e.g. labour hours, capital quality and deflator problems). Other studies use patents but, as is well-acknowledged, by no means all new knowledge is patented. As Griliches has pointed out, the service sector of the economy, for example, has very little patenting, but, many argue produces new knowledge in the form of unpatented product and process innovations: new brand names and new retailing formats for example. Second, measuring use of the existing knowledge stock is also problematic. What is required is the importance-weighted stock and hence a key indicator that has been developed is citations. This refers to patented innovations and so might not cover the knowledge flows from other sources e.g. marketing information from head offices etc. Recent work has also highlighted the problem that citations are entered both by the inventor and patent examiners potentially obscuring the idea flows used by the inventors themselves.

Our approach in this paper is to use a new data set on innovations, R&D and innovation-related knowledge flows. We use two waves of the Community Innovations Survey (CIS), an EU-wide survey set up following the guidelines agreed in the OECD Oslo manual. The survey asks firms to report a number of different knowledge outputs, such as patenting, product and process innovations and organisational innovations. It also asks firms to report on inputs. There are two main types of inputs: spending on R&D and other innovation-related inputs and the importance of knowledge flows, in particular from within the firm or enterprise and from outside. Thus, whilst these data have their problems, which we discuss below, we think they are of interest in that they do confront the two existing data problems mentioned above. First, they use other measures of innovations beside patents and TFP growth and second, they do have different measures of knowledge flows to patent indicators that are importance weighted.

We match these data to indicators of global engagement and study three issues. Firstly, on these data, are more globally engaged firms more innovative, measuring innovations in different ways? Secondly, do globally engaged firms use more inputs to innovation such as scientists or information flows? We find the answer to be yes to both these questions. This leads to the third question, namely how much of the innovation output advantage of globally engaged firms is explained by the increased use of inputs? The answer to this question varies according to the output measure used.

There are (at least) two key objections to our data. Firstly, whilst it might be thought desirable to have wider data on innovations than patents, data on self-reported product and process innovations might be regarded as inaccurate. For this reason we use a number of different measures of innovations, including the more conventional one of patents. Secondly, the information flow variables are responses to questions asking firms to rate the importance of various sources of knowledge. Such reports might also be felt to be inaccurate and, being qualitative, of dubious value. We discuss this more in the analysis but briefly the question is what would be the best measure of knowledge flows, especially between plants within a firm? Knowledge flows are presumably many and various, consisting of the sharing of technological and marketing information, advice over the telephone, videoconferencing, site visits by company experts etc. Little of this would be captured by patent citations, either because marketing knowledge is not patentable, or because only additions to knowledge might be patented which would not capture the sharing of information about existing patentable innovations. More quantitative evidence might be gleaned from payments within firms, e.g. patent royalties, but within-firm monetary transfers might be poorly measured due to transfer pricing incentives, as well as missing the other types of knowledge flows due to within-firm contacts. Other quantitative data might be generated by collecting information on e.g. email traffic, phone calls and travelling by purpose but such forensic data has not, to the best of our knowledge, been collected. Thus qualitative evidence might be, for the moment, a useful summary measure of the plethora of information flows within the firm.

The findings confirm the prediction of the traditional multinational theories (e.g. Caves (1996) and Markusen (2002)) that multinational firms are more innovative and share knowledge within the enterprise group more than other firms. The results also seem to suggest that foreign affiliates use knowledge produced by other firms in the group, more than UK MNEs do, again in line with the predictions of the knowledge capital theory of multinationals. We also find evidence that exporting firms have an innovative lead over non-exporting firms.

The rest of this chapter proceeds as follows. Section 2 sets out the data description and summary tables; section 3 describes the econometric framework for estimating the Knowledge Production Function using a number of different innovation measures. Section 4 sets out our results and section 5 concludes.

4.2 A Theoretical Framework of Knowledge Production

4.2.1 A KPF organising framework for summary statistics

Like a production function for goods and services, the innovation production function relates inputs into the innovation process to outputs. Following Griliches (1979), we can model ΔK, the change in knowledge stock as:

$$\Delta K_i = f(H_i, K') \tag{4.1}$$

where ΔK is the change in knowledge stock, K' is flow of ideas to the plant from the existing stock of ideas into the change in the knowledge stock and H is inputs into the process of knowledge creation – e.g., equipment or the human capital of R&D scientists. The subscript i is used to index variously countries, industries, or plants; for our study, it will index plants within a country (for us, the United Kingdom). Unlike physical equipment knowledge can potentially flow across firms. Thus K' might usefully be written:

$$\Delta K_i = f(H_i, K'_i, K'_{-i}) \tag{4.2}$$

where K'_i and K'_{-i} indicate the flow of ideas from within and outside the plant. Thus for example an idea developed elsewhere in a multi-plant firm which plant i shares in would be part of K'_i. Some specifications of 4.2 are special cases. For example, some specifications write K rather than K'. This assumes that each existing idea is equally important to all firms. Consider, for example, the stock of knowledge at an industry trade fair or at a university. Each firm visiting the trade fair or co-operating with a university may or may not gain ideas from such forums because not all ideas are of equal importance to all firms. For patentable innovations this is the motivation for using citation-weighted patents. Other specifications do not subscript K by i, meaning that scientists in unit i all have access to the same knowledge stock. In the light of 4.2, we wish to explore different measures of ΔK, H_i, K_i' and K_{-i}' and the extent to which differences in ΔK are explained by differences in the inputs H_i, K_i' and K_{-i}'.

4.3 Data Description and Summary Statistics

Our empirical analysis uses data on U.K. firms constructed from three key data sources. First is the U.K. Community Innovations Survey. This is an EU-wide survey developed to measure both innovative output and inputs of firms. It also collects data on exporting. The other two data sources are the Annual Inquiry into Foreign Direct Investment (AFDI) and the Annual Respondents Database (ARD), both of which are used to identify each of our U.K. CIS observations as a parent of a U.K.-based multinational or an affiliate of a foreign-owned multinational. We briefly discuss each data source.

4.3.1 CIS Data

The U.K. CIS is part of an EU-wide survey that asks companies to report the output of their innovation efforts (introduction of innovative new products and/or processes; percentage of sales arising from new and improved products; and "soft" innovations, such as organisational change); the firm's inputs to innovations (R&D, scientists, etc.) and the sources of knowledge for innovation efforts. There have been three waves of U.K. CIS surveys: CIS1 (covering the period 1991-93), CIS2 (1994-96) and CIS3 (1998-2000). Our work covers CIS3 and CIS2 (the response rate on CIS1 was around 10% and is not suitable for analysis).

The CIS is a voluntary postal survey carried out by the Office of National Statistics (ONS) on behalf of the Department of Trade and Industry (DTI). ONS selects survey recipients by creating a stratified sample of firms with more than 10 employees drawn from the Inter-Departmental Business Register (IDBR) by SIC92 two-digit classes and eight employment-size bands. The survey covers both the production and the service sectors.[2] CIS3 was in the field twice: the first wave sampled 13,340 enterprises, and the second top-up covered 6,285 to make the sample representative at the regional level. Of the total 19,625 enterprises to which the survey was sent, 8,172 responded (3,605 in services and 4,567 in production), for an overall response rate of 42%. For CIS2 5,892 were sampled and 2,342 responded; accounting for bankruptcy, this was a response rate of 43.2%. Manufacturers and service sector companies were sent very slightly different questionnaires ; replies and response rates were 1,596 and 743, 41% and 37% respectively.[3]

Two important issues immediately arise from the sample design of the CIS. First is the question of non-response.[4] Since the survey is voluntary and postal, there is the risk of low-response and thus of non-response bias. For CIS3 (we were not provided with the sampling frame for CIS2) we investigated the characteristics of respondents and non-respondents using the CIS survey universe matched with the ARD data. Non-respondents were on average larger than respondents, both in terms of turnover and employment. In our regressions below we control for size. In the summary statistics we do not weight so the averages therein should not be regarded as representative of the whole economy.

Second, the survey was conducted at the enterprise level; where enterprise is defined as "the smallest combinations of legal units which have a certain degree of autonomy within an enterprise group." Thus, an enterprise is roughly a firm, where each firm can have more than one business establishment and can also be part of a larger multi-enterprise business entity called an enterprise group. For our interest in globally engaged firms, by construction any U.K. enterprise that is part of a multinational firm has at least one other enterprise in its enterprise group somewhere in the world. One might worry about reporting error due to respondents not answering at the desired enterprise level. We were able to identify small numbers of such probable cases through data checking and cleaning; our results appear to be

[2]Production includes manufacturing; mining; electricity, gas and water; and construction. Services includes wholesale trade; transport, storage, and communication; and financial intermediation and real estate.

[3]A final response rate of 40% is in line with response rates to CIS in other European countries, where answering the survey was not compulsory (e.g. Germany, Spain and Belgium).

[4]To boost response enterprises were sent the survey, posted a reminder, posted a second reminder (with the survey again) and finally telephoned.

robust to this issue.[5]

Regarding the contents of the data, the essential idea of the survey is to get enterprises to retrospectively report separately "technological" and "organisational" innovations (with separate questions for each group). In turn, technological innovations are split into process and product innovations. Appendix C sets out the survey questions for both product and process innovations and patents. For product and process innovations, the CIS questionnaire provided additional information to respondents (e.g., providing an example of what is and is not an innovation) to clarify definitions and thereby improve response quality. A potential problem with this approach is its subjective nature. Since companies are asked about products or processes that are "technologically new", there is obvious scope for differences in interpretation even with guiding information provided in the questionnaire. For example, some firms might report "yes" to all questions to not be seen as somehow backward which induces measurement error in the innovation measure and possibly an artificial positive correlation between innovation outputs and inputs. There are a number of points worth noting in this regard. First, as we shall show 70% of firms report performing no innovation at all, so there is at least some reporting of zero innovations. Second, of those reporting no innovation at all, about 26% report positive innovation inputs, suggesting that for these respondents at least they do not "boost" their replies to every question. Third, we shall also present results for patents which are less likely to be so subjective.[6]

Finally, one might worry that the person answering the questionnaire might not have the knowledge to represent accurately the true position of the firm. Some researchers have recommended multiple sampling of persons within the organisation to overcome this but with a sample of almost 20,000 enterprises this is infeasible. The ONS does keep on its mailing list specific contact persons to whom it addresses data requests and the CIS was sent to these people where identified. We do not however have access to the mailing list to check on responses from firms with a

[5]These robustness checks consist, for example, in leaving in the sample only single-plant firms. Indeed, a misunderstanding can arise only for multi-plant firms and/or firms that are part of an enterprise group.

[6]One check on these responses is that companies are asked to fill out in long-hand their "most important product or process". The long-hand response rates were not high (about 30%) but our casual inspection of these responses relative to the guidelines provided indicated that enterprises were able to report technological innovations.

specific addressee and those addressed to e.g. the company secretary, so this remains an open question.[7]

4.3.2 AFDI and ARD Data

The CIS measures one dimension of the global engagement of firms in that it asks whether and how much firms exported in 1998 and again 2000. But it does not have any information on the other key dimension of global engagement: being part of a multinational firm. Accordingly, to add this information to the CIS data we merged in nationality of ownership data from the AFDI and ARD.

The AFDI is an annual survey to businesses which requests a detailed breakdown of the financial flows between UK enterprises and their overseas parents or subsidiaries. It contains an "outward" part that measures outward FDI by U.K. parents and also an "inward" part that measures FDI into the U.K. by foreign-owned firms. To run the AFDI, ONS maintains a register that holds information on the country of ownership of each enterprise and on which U.K. enterprise has foreign subsidiaries or branches. This register is designed to capture the universe of enterprises that are involved in FDI abroad and in the UK, where a 10% ownership stake is applied in both directions. It is continuously updated from a variety of government and private-sector data sources.

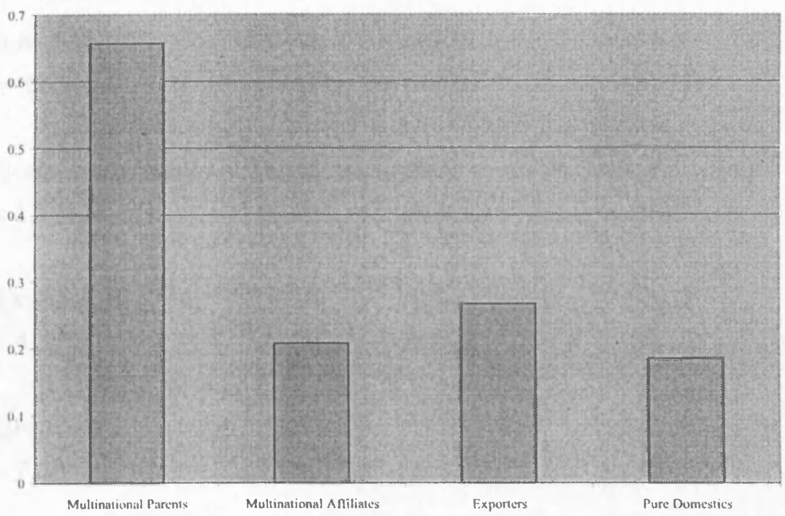
The ARD provides an alternative source of information on the country of ownership of foreign-owned firms operating in the U.K., where here the underlying data source is solely Dun & Bradstreet Global "Who Owns Whom" database. The AFDI and ARD methods differ in two potentially important respects: AFDI tracks the nationality of direct owners using a threshold of 10%; ARD tracks the nationality of ultimate owners using a threshold of 50%. In principle then, these two different data sets can yield different answers as to whether a U.K. firm is foreign owned and if so, by a firm in which country. In practice, there were very few such discrepancies in our data: only about two dozen firms classified as foreign owned by AFDI but not by ARD. We chose to use the AFDI categorization in these "conflicting cases", both to maximize the number of foreign-owned observations and because its 10% ownership criterion is widely used by statistical agencies in other countries (e.g., the United

[7] However, the problem of biased response is perhaps more important in attitudinal surveys e.g. questions about the friendliness of industrial relations.

States' Bureau of Economic Analysis). In practice, our results are robust to giving precedence to the ARD scheme. We were able to merge accurately the AFDI and ARD data into the CIS data since the ONS used the same core set of firm and group identifiers for all three data sets. With all this information combined, we created four categories of global engagement for our firms: parents of U.K. multinationals; affiliate of foreign multinationals; non-multinational firms that export; and "purely domestic" firms that neither export nor are part of a multinational.[8]

4.3.3 Summary Statistics

Figure 4.1: Average Patents per R&D Employee



For our benchmark sample of 7,385 enterprises we ended up with the following distribution: 577 multinational parents (7.8% of the sample); 653 multinational affiliates (8.8%); 1,776 non-multinational exporters (24.0%); and 4,379 purely domestic enterprises (59.3%). Consistent with many of the studies cited in the introduction, in our sample there are basic performance differences across these four groups. For example, mean size (either sales or employment) and capital intensity are highest for the parents and the affiliates, then the exporters, and finally the purely domestics. There are also differences in the industry and regional distribution of these

[8]There were also a small number of firms that were classified as U.K. parents in the AFDI data but also U.K. affiliates in the ARD data. In principle, such complicated ownership structures can be found given the nature of the two data sets. In practice, to maximize our number of U.K. parents we placed this small number of firms in the U.K.-parent category. Our results below were robust to the alternative of placing them in the U.K.-affiliate group.

Table 4.1: Summary Statistics on Knowledge Outputs

SubSample	Innovate	Patent Protect	% New and improved Sales	Patents
Multinational Parents	0.45	0.32	0.1	10.02
(N = 577)	(0.5)	(0.47)	(0.20)	(159.64)
Multinational Affiliates	0.42	0.37	0.1	2.78
(N = 653)	(0.49)	(0.48)	(0.21)	(15.54)
Non-Multinational Exporters	0.38	0.23	0.1	0.82
(N = 1,776)	(0.49)	(0.42)	(0.21)	(5.58)
Purely Domestics	0.18	0.06	0.04	0.1
(N = 4,379)	(0.39)	(0.23)	(0.15)	(2.03)
All Enterprises	0.27	0.15	0.06	1.37
(N = 7,385)	(0.45)	(0.36)	(0.18)	(46.64)

Notes: For each cell, indicated summary statistics are means (and standard deviations in parentheses). *Innovate* is an indicator variable equal to one if enterprises reported any process or product innovation. *Patent Protect* is an indicator variable equal to one if enterprises reported either applying for new patents 1998-2000 or using existing patents to protect innovations. *% New and improved Sales* is the share of enterprise sales in 2000 accounted for by new and improved products. Patents is the number of patents applied for over the 1998-2000 period. The 7,385 total enterprises in this table corresponds to the number of observations in the benchmark regressions in Table 2. See text for data details.

Table 4.2: Summary Statistics on Knowledge Inputs

SubSample	% R&D Personnel	% Scientists	Intramural R&D Intensity
Multinational Parents	0.04	0.1	0.016
(N = 577)	(0.1)	(0.17)	(0.057)
Multinational Affiliates	0.04	0.12	0.012
(N = 653)	(0.12)	(0.18)	(0.048)
Non-Multinational Exporters	0.03	0.08	0.016
(N = 1,776)	(0.08)	(0.17)	(0.059)
Purely Domestics	0.01	0.04	0.006
(N = 4,379)	(0.07)	(0.13)	(0.042)
All Enterprises	0.02	0.06	0.01
(N = 7,385)	(0.08)	(0.15)	(0.05)

Notes: For each cell, indicated summary statistics are means (and standard deviations in parentheses). R&D Personnel is number of enterprise workers involved in R&D activities in 2000. % R&D Personnel is the share of enterprise employment in 2000 accounted for by R&D workers. % Scientists is the share of enterprise employment accounted for by degree-level or above workers in science and engineering subjects. Intramural R&D intensity is the ration of the value of R&D performed by the enterprise in 2000 over sales in 2000. The 7,385 total enterprises in this table corresponds to the number of observations in the benchmark regressions in Table 4.4. See text for data details.

Table 4.3: Summary Statistics on Knowledge Flows

SubSample	Internal Self	Internal Group	Vertical	Competitor	Free	University
Multinational Parents	0.51	0.32	0.5	0.29	0.39	0.19
(N = 577)	(0.67)	(0.33)	(0.67)	(0.33)	(0.33)	(0.00)
Multinational Affiliates	0.49	0.4	0.48	0.29	0.38	0.2
(N = 653)	(0.67)	(0.33)	(0.67)	(0.33)	(0.33)	(0.00)
Non-Multinational Exporters	0.45	0.19	0.46	0.25	0.35	0.13
(N = 1,776)	(0.33)	(0.00)	(0.67)	(0.00)	(0.33)	(0.00)
Purely Domestics	0.23	0.1	0.3	0.15	0.23	0.06
(N = 4,379)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
All Enterprises	0.33	0.16	0.37	0.2	0.29	0.1
(N = 7,385)	(0.00)	(0.00)	(0.33)	(0.00)	(0.00)	(0.00)

Notes: For each cell, indicated summary statistics are means (and medians in parentheses). Each variable is a categorical indicator of how important a different knowledge source is to the enterprise's innovation activities. Each variable takes possible values of 0, 1/3, 2/3, and 1; higher values indicate greater importance for an information source. *Internal Self* measures knowledge inside the enterprise itself. *Internal Group* measures knowledge inside the broader business group of affiliated enterprises. *Vertical* measures knowledge from customers or suppliers. *Competitor* measures knowledge from competing firms. *Free* measures knowledge from professional conferences and exhibitions. *University* measures knowledge from universities. See text for data details.

firm types. These sorts of performance differences will be accounted for in our econometric analysis, but not in our simple summary statistics.

Tables 4.1, 4.2 and 4.3 present means and standard deviations or medians (as reported in the notes) on innovation outputs, inputs, and flows for our entire sample of enterprises and also our four sub-samples by global engagement. There are three important messages from these tables. Firstly, globally engaged enterprises create substantially more new ideas than do purely domestic enterprises. Our broadest and thus benchmark measure of knowledge output is *Innovate*, an indicator variable equal to one if enterprises undertook any process or product innovation. Appendix C reports the exact survey question for these two parts of Innovate, as well as for all the other variables. About 45% of all multinationals and 42% of all exporters report having innovated. In contrast, only 18% of purely domestic enterprises report innovating. A similar contrast appears for alternative measures of knowledge output. Column 2 shows a similar pattern for *Patent Protect*, a binary variable equal to one if the enterprise either applied for new patents during 1998-2000 or used existing patents to protect its innovations. In column 3 the knowledge measure is *% New and improved Sales*, the share of enterprise sales in 2000 accounted for by new and improved products. Column 4 again shows a similar pattern for the number of new patents applied for over the 1998-2000 period, Patents.[9] We found many of the two-way differences (for brevity, not reported) to be statistically significant. For example, for all four measures multinational parents create more knowledge than do domestic enterprises. We note that for all sub-samples and all knowledge measures, the median enterprise reports no knowledge outputs. That said, the distribution of innovation is less skewed for our broader measures than for Patents. For example, the number of all enterprises reporting "yes" for Innovate is nearly twice the number that have some patent protection, and about four and a half times the number that applied for new patents. As discussed earlier, we think one of the merits of our study is not just its multiple measures of innovation, but also that many of these measures look broader than the commonly used counts of patents.

The second important message of Table 4.2 is that globally engaged enterprises

[9]Note that Patent Protect we regard to be a broader output measure than Patents. Given that many enterprises generate patentable innovations infrequently, an enterprise might protect exiting patents-and thus be considered innovative-even if it did not recently apply for new patents.

use more inputs for making new ideas. Column 1 and 2 of Table 4.2 show this for R&D Personnel and scientists and engineers: column 1 reports % R&D Personnel, the share of enterprise employment in 2000 accounted for by R&D workers. The same pattern applies: this share is three to four times greater for globally engaged enterprises. Innovative activity is often thought of as the domain of workers in science and engineering occupations. This may be true for some enterprises and sectors, but is likely false for others in our data. In particular, innovation in many service sectors such as finance and retail trade is likely performed by non-science, non-engineering occupations. Despite this preference for using R&D personnel as our "headcount" measure of innovation inputs, column 2 reports % Scientists, the share of enterprise employment accounted for by degree-level or above workers in science and engineering subjects. This is not quite the same as science and engineering occupations (as workers in these occupations could have different educational backgrounds, and/or workers with such education need not work in those occupations). That said, the same pattern appears here as for share of R&D workers: for all three categories of globally engaged enterprises about 10% of workers have science or engineering degrees, versus just about 4% for domestics. The last column of Table 4.2 reports Intramural R&D intensity, the share of sales spent in R&D by the enterprise in 2000. This measure of knowledge inputs captures not just expenditures on personnel but also on the complementary capital (see Appendix C). Multinational enterprises and exporters average 0.16%, versus 0.06% for purely domestic firms. As with Table 4.1, many of the two-way differences (for brevity, not reported) we found to be statistically significant. For example, for all four measures both multinational parents and affiliates use more knowledge inputs than do domestic enterprises. The production-function framework motivating our analysis suggests that some of the variation in knowledge outputs in Table 4.1 can be accounted for by variation in knowledge inputs in Table 4.2.

Table 4.3 suggests that this is not the whole story. Here we report both where enterprises learn information for innovation and how important are these sources. For each of the information categories across Table 4.3, each enterprise was asked to report whether any information from this source was used in its innovative activities and, if so, whether the importance of this source was low, medium, or high. This information was codified from 0 to 3 on a 4-Likert-Scale. We rescaled the responses into a categorical variable of values 0, 1/3, 2/3, and 1 going from no information to information of high importance.[10] Mean (and median) responses are reported. The first two columns of 4.3 cover information internal to the enterprise itself (Internal Self) and information internal to the enterprise's broader enterprise group (Internal Group). By definition, any enterprise that is part of a multinational has a broader enterprise group elsewhere in the world. For Internal Self, we see that globally engaged enterprises report much higher mean (and median) importance for this information source. The same is true for Internal Group – where it is also very notable that the mean value for affiliates is higher (statistically significantly so) than that for parents. This accords with the now-standard knowledge-capital model of multinationals in international trade, which assumes both that knowledge is created predominantly by parents and that intra-firm knowledge flows are predominantly from parents transferring knowledge and related firm-specific assets to affiliates. Looking across all columns of Table 4.3 shows the same pattern of globally engaged enterprises learning more than do their domestic counterparts. Indeed, the medians across all columns are striking: the median globally engaged firm learns at least something from five information sources, whereas the median purely-domestic firm learns nothing from all six.

We conclude that firms differ along all three dimensions of the knowledge production function: knowledge outputs, knowledge inputs, and access to flows of existing knowledge. This last difference contradicts the assumption of some literatures that in equation 4.2 all firms have equal access to the same flows of knowledge. It suggests that in estimating knowledge production functions it will be important to account for these differences. We can visualize this important point about access to knowledge. Much theory work on ideas in the macro-growth literature assumes both a single world knowledge stock and a Cobb-Douglas formulation for equation 4.2, in which case it follows that all knowledge workers should have the same average labor productivity (adjusted as needed for the Cobb-Douglas technology parameter on labor; see Jones, 2003). Is this true in the data? Tables 4.1 to 4.3 suggest that the answer is no. Figure 4.1 shows that it is not. For each of the four groups of globally engaged firms, this figure plots the average number of patents per R&D worker. The important message is that globally engaged firms have more patents

[10]The details of the construction of this variables are described in more detail in Appendix C.

per knowledge worker than do the purely domestic firms; this is consistent with the evidence in Table 4.3.[11]

4.4 Econometric Strategy and Estimation Results

4.4.1 Econometric Strategy

In this section we describe our measures of ΔK and the different implications for econometric work. The next section sets out the results.

Our first measure is a binary variable that takes value one whenever the firm reports either a process or product/service innovation. Since this is a dependent binary variable we estimate our KPF using probits. This raises a number of issues. Firstly, the coefficients of a probit equation do not measure marginal effects. Thus, we report the marginal effects calculated as:

$$\frac{\partial E(y|x)}{\partial x_j} = \beta_j \phi(x\beta)$$

where ϕ is the normal density function and we estimate the marginal effects at the mean values of the regressors. We report the standard errors of the marginal effects calculated using the delta method. A second issue concerns the possibility of calculating elasticities from either the probit coefficients or the marginal effects. As noted by Wooldridge (2002), it does not seem possible to recover a formula for the elasticity in respect to the underlying latent variable y^*. The only parameter that one might be able to recover is the partial effect of the regressors on the probability that the observed binary variable takes value one.

Finally, a third concern is endogeneity. Regressors such as H may be correlated with the regression error if an unobserved effect on innovation also affects H. Such effects could be due to an underlying unobserved firm fixed effect and/or an idiosyn-

[11]For each of the four firm groups Figure 4.1 reports that group's total number of patents (i.e., the sum across firms of Patents) divided by that group's total number of R&D workers. Alternative methods for calculating each group's average productivity (e.g., calculating the productivity per firm and then averaging these productivities across all firms) yield very similar results. Figure 4.1 implicitly assumes constant returns to knowledge workers for the Cobb-Douglas version of equation 4.2. If one assumes greater degrees of decreasing returns to scale to knowledge workers, then the analogous differences in Figure 4.1 become even larger (because the number of R&D workers needs to be raised to a power less than one before dividing into number of patents).

cratic shock. The bias could be positive or negative depending on whether the effect on innovation increases or reduces the marginal product of staff. We estimate all our regressions with industry dummies so control for fixed effects that are common within industries. We go further in two regards, instrumental variables and panel regressions. Concerning the first, the use of IV with a limited dependent variable (discrete or censored) is not straightforward. We use the AGLS method as proposed by Amemiya and implemented by Newey (1987) (see also Maddala (1983) pp. 247-252).

To construct an instrument for H we used information from the CIS2 survey namely the unweighted averages of the level of R&D employees at the 4-digit industry level and the unweighted averages of the proportion of R&D employees at the 4-digit industry. Note that these instruments are built excluding those firms that are both in CIS2 and CIS3. The rationale behind the choice of the instrument is that the lagged level (and proportion) of R&D employees at the 4-digit level is likely correlated with each company's "normal" demand for R&D workers but hopefully uncorrelated with company-specific unobservables (e.g., management or productivity shocks) that would cause differences in R&D personnel from its normal level that would also be correlated with innovation outcomes. The rationale behind excluding the firms that are both in CIS3 and CIS2 is that if the source of the endogeneity is the correlation between the firm fixed effects and the R&D personnel variable, lagged level of R&D personnel at the 4-digit industry levels, which include lagged R&D personnel at the firm level, will not be valid instruments. We did experiment with different aggregation levels (e.g. 3-digit rather than 4 digit, use averages within regional and size cells as well as industry, etc.). An evident trade-off with the instruments is that the more refined the IV the higher the predictive power of the instrument, but the less overlap of cells between CIS2 and CIS3. We did test for the strength of these instruments by regressing our endogenous variable, level of R&D personnel on a set of exogenous variables (regional dummies, 2-digit industry dummies, the GE variables, exporter, UK MNE, and foreign; size and the information variables) and the two instruments proposed. The coefficients on the instruments were both strongly significant.

A second approach to addressing the endogeneity problem is to use panel data methods. We constructed a CIS panel using the overlap of about 780 firm between

CIS2 and CIS3 (see Appendix C for details). However, there are both data related and econometric issues with this approach. Regarding data issues, first the ordering and the phrasing of the questions have changed somewhat between the two surveys. For example, in CIS3 firms are asked about patents applied for and also whether they used patents to protect their innovation, in CIS2 they are not asked the latter. Regarding econometric issues, first the set of firms present in both CIS2 and CIS3 is a self-selected sample of surviving firms. Suppose that the relation between innovation output and innovation inputs is positive and that survival is greater for innovating firms. Then selecting a group of surviving firms selects, among the firms with low innovation and human capital, only those firms who have had a positive shock to innovation. This then flattens the expected relation between innovation and innovation inputs. Thus the possible reduction in the effects of innovation inputs due to controlling for fixed effects might be overstated by the reduced effect due to selection. The second set of econometric issues arise from the incidental parameters problem in non-linear models.[12] The fixed effects maximum likelihood estimator is inconsistent when T is fixed. As Greene (2004) notes, how serious these problems are in practical terms remains to be established - there is only a very small amount of received empirical evidence and very little theoretical foundation. However, his simulations suggest in T=2 very substantial bias (of the order of 100%) to coefficients in probit models. Thus there are a number of ways forward. One is to use the pooled estimator, rather than the random or fixed effect models(Greene, 2004). Another is to use the conditional logit model (Chamberlain, 1984), where the functional form allows one to estimate the parameters of interest without having to estimate the incidental parameters. Note that in the conditional logit identification is provided only by firms who switch their innovation status: all firms with unchanged innovation output drop out of the conditional likelihood function. In our sample of 787 "panel" firms we observe 361 changes. Thus, the number of useful observations is smaller, and hence estimation less precise for the conditional logit estimator. Note too that another limitation is that we cannot estimate marginal effects in this model.

The second measure of innovation outcome of firms we use is the number of

[12]In linear models, the incidental parameters i.e. the fixed effects are eliminated by differencing or by taking deviations from group means. This option is unavailable in non-linear models.

patents applied for. This variable only takes on non-negative integer values, thus we can use count data models to estimate the innovation production function in this case. In particular, we decide to use a negative binomial model (Cameron and Trivedi, 1986), which, relative to a Poisson model, relaxes the variance-mean equality assumption.

In the negative binomial model, the estimated coefficients corresponds to semi-elasticities. Thus, we can derive both the marginal effects and the elasticities from the estimated coefficients. For x continuous,

$$\beta_j = \frac{\partial E[y|x]}{\partial x_j} \frac{1}{E(y|x)}$$

the marginal effects is: $\frac{\partial E[y|x]}{\partial x_j} = \exp(x\beta)\beta_j$

and similarly we can calculated the elasticity at the sample mean by multiplying the coefficient by the average x_j in the sample. As for endogeneity, we used panel data methods and we estimate a fixed effect negative binomial model, by conditional maximum likelihood.

4.4.2 Estimation Results

The estimation results of equation 4.2 for the two measures of innovation used, *Innovate* and *Patents* are reported in tables 4.4 and 4.5, respectively. As discussed earlier, these two dependent variables present a basic trade-off of breadth versus quantification. We have a qualitative measure of knowledge output, Innovate, which enjoy the advantage of measuring innovation more broadly. We have a quantitative measure of knowledge output, Patents, which is a count variable, rather than dichotomous, but it measures knowledge output more narrowly than the previous one. We will start with the broader measure.

Table 4.4 reports regression results for several specifications of the knowledge production function in equation 4.2, all of which use as the regressand our baseline knowledge-output measure Innovate. Columns 1-5 and 7-8 of Table 4.4 are estimated via probit, column 6 by IV probit, and column 9 by conditional logit. All rows in a column report the marginal impacts (and robust standard errors, clustered on firm within an enterprise group) for the indicated regressor, except for column 9 which reports coefficients not marginal effects (see above). All specifications in Table 4.4 include a common set of control regressors (not reported for brevity) to help control for plausibly important cross-firm sources of innovative heterogeneity: a full set of two-digit industry dummies (approximately 50 controls), a full set of regional dummies (12 controls); firm size (measured as total employment), and a categorical indicator for enterprise's Structural Changes (to account for patterns such as newly-born start-up firms being more likely to innovate a lot).

Table 4.4: Estimates of the Knowledge Production Function for Output Measure Innovate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exporter	0.1463	0.1455	0.0470	0.0817	0.0461	0.0624	0.0208	0.0472	0.0294
	(0.0149)***	(0.0154)***	(0.0140)***	(0.0148)***	(0.0140)***	(0.0174)***	(0.0207)	(0.0154)***	(0.5316)
Multinational Parent	0.2204	0.1902	0.0706	0.0907	0.0617	0.0766	0.0840	0.0985	1.0433
	(0.0248)***	(0.0266)***	(0.0241)***	(0.0250)***	(0.0238)***	(0.0273)***	(0.0244)***	(0.0251)***	(0.6691)
Multinational Affiliate	0.1871	0.1496	0.0528	0.0513	0.0365	0.0631	0.0518	0.0589	0.3921
	(0.0223)***	(0.0238)***	(0.0209)**	(0.0219)**	(0.0206)*	(0.0256)**	(0.0221)**	(0.0215)***	(0.6182)
R&D Personnel		0.0073	0.0018	0.0026	0.0018	0.0018	0.0009	0.0016	0.0032
		(0.0023)***	(0.0006)***	(0.0009)***	(0.0006)***	(0.0009)*	(0.0005)	(0.0007)**	(0.0092)
Vertical Info.			0.3173	0.4665	0.3143	0.3306	0.1316	0.4092	0.9092
			(0.0217)***	(0.0214)***	(0.0218)***	(0.0252)***	(0.0361)***	(0.0241)***	(0.6236)
Competitors' Info.			-0.1129	-0.1356	-0.1236	-0.1286	-0.0085	-0.1141	-0.8656
			(0.0219)***	(0.0233)***	(0.0222)***	(0.0253)***	(0.0314)	(0.0247)***	(0.6671)
CommercIal Info.			0.0608	0.0898	0.0541	0.0584	-0.0315	0.0530	-0.0921
			(0.0221)***	(0.0229)***	(0.0222)**	(0.0250)**	(0.0314)	(0.0245)**	(0.6241)
Free Info.			0.1295	0.1620	0.1287	0.1410	0.0074	0.1372	0.4548
			(0.0225)***	(0.0230)***	(0.0225)***	(0.0257)***	(0.0342)	(0.0250)***	(0.6595)
Regulatory Info.			-0.0436	-0.0019	-0.0473	-0.0644	-0.0268	-0.0394	0.0462
			(0.0198)**	(0.0201)	(0.0197)**	(0.0226)***	(0.0269)	(0.0214)*	(0.5139)
University Info.			0.0002	0.0358	-0.0037	0.0121	0.1206	0.0379	0.0640
			(0.0270)	(0.0288)	(0.0270)	(0.0400)	(0.0356)***	(0.0290)	(0.7639)
Government Info.			0.0044	-0.0083	0.0004	-0.0101	-0.1053	-0.1045	0.5482
			(0.0284)	(0.0299)	(0.0284)	(0.0358)	(0.0336)***	(0.0292)***	(0.7417)
Internal Info.– Self			0.3594		0.3489	0.3801	0.2031	0.4092	1.8032
			(0.0181)***		(0.0184)***	(0.0216)***	(0.0298)***	(0.0201)***	(0.5136)***
Internal Info. - Group				0.1406	0.0647	0.0781	-0.0015	0.0535	-0.3549
				(0.0199)***	(0.0193)***	(0.0250)***	(0.0263)	(0.0214)**	(0.5983)
CIS Wave	3	3	3	3	3	3	2	2 and 3	2 and 3
Enterprise Fixed Effects	No	No	No	No	No	No	No	No	Yes
Observations	7,385	7,385	7,385	7,385	7,385	5,999	1,787	9,172	494

Notes: *Innovate* is an indicator variable equal to one if enterprises reported any process or product innovation. Each column is a different estimated specification, with each row in columns (1) through (8) reporting the marginal impacts (and robust standard errors, clustered by enterprise group) for the indicated regressor as estimated by probit (IV probit in column (6)). Column (9) reports estimated coefficients (and standard errors) from a conditional logit estimator. *, **, and * * * indicate statistical significance at the 10%, 5%, and 1% levels. All specifications include additional control regressors (not reported for brevity): two-digit industry dummies; 12 regional dummies; enterprise total employment; a categorical indicator of structural change (see Appendix C); and for columns (8) and (9) a CIS Wave indicator.

Column 1 estimates the knowledge production function with only the GE dummies. They are all statistically significant. Furthermore, they are quantitatively significant. The coefficient on MNE parent for example indicates that MNE parents are 22 percentage points more likely to innovate relative to the domestic firms (the omitted category). Recall from Table 4.1 that in the raw data such firms are 27 percentage points (0.45-0.18) more innovative on average, so the dummies in this regression are explaining the bulk of this difference. Note too that all these regressions include employment numbers and industry, region and start-up dummies; as we shall see later these variables account for almost all of the variation in patents but little of the variation in this broader innovation measure.

Column 2 adds to the production function in Column 1 our H indicator, namely R&D personnel. This is positive and statistically significant, but reduces the coefficients on the dummies only slightly. To get some idea of the quantitative significance, the gap between R&D employment in domestic and MNE parents is 26.16-0.62=24.53 (data from Table 4.2). Multiplying this by the coefficient in Table 4.4 column 2 (0.0073) gives an implied probability difference of 19 percentage points, which is quantitatively significant.[13]

Both these specifications omit however the information flow variables that the KPF suggests are important determinants of ΔK and are plausibly correlated with H and GE. Thus in column 3 we add the information flow variables, here using only reported internal information from the own enterprise. Columns 4 and 5 add information flows from the enterprise group and from both enterprise and group respectively. A number of common findings appear in these columns. First, the coefficient, although not the significance of the GE dummies is cut to about one third of its previous value. Second, there is a similar reduction in the coefficient on H. Thus including these information flow measures matters greatly. Third, many of the information dummies are statistically significant. Internal information from the own enterprise for example has a higher marginal effect than information from the enterprise group and vertical information is positive and significant as well,

[13]Note in passing that this column allows one to test a maintained assumption in some of the macro/growth literature, namely that the global stock of knowledge is equally accessible to all firms. If this were so then these global-engagement indicators should be individually and jointly insignificantly different from zero, with differences in ΔK explained only by differences in H. The data reject this hypothesis.

Table 4.5: Estimates of the Knowledge Production Function for Output Measure Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exporter	0.2128	0.2510	0.0639	0.0867	0.0660	0.7895	0.1779	1.1556
	(0.0546)***	(0.0593)***	(0.0171)***	(0.0211)***	(0.0176)***	(0.2112)***	(0.0391)***	(0.7444)
Multinational Parent	0.7421	0.6004	0.0871	0.1460	0.0857	0.9390	0.2455	0.8776
	(0.2698)***	(0.1724)***	(0.0332)***	(0.0555)***	(0.0329)***	(0.4718)**	(0.0844)***	(0.7945)
Multinational Affiliate	0.5157	0.4815	0.1136	0.0996	0.1054	1.1513	0.2154	1.1902
	(0.1840)***	(0.1551)***	(0.0380)***	(0.0372)***	(0.0366)***	(0.4164)***	(0.0680)***	(0.8148)
R&D Personnel		0.0038	0.0005	0.0006	0.0005	0.0015	0.0011	0.0062
		(0.0019)**	(0.0002)**	(0.0003)**	(0.0003)**	(0.0022)	(0.0005)**	(0.0043)
Vertical Info.			-0.0039	0.0311	-0.0075	-0.7704	-0.0179	0.8206
			(0.0131)	(0.0143)**	(0.0132)	(0.2238)***	(0.0341)	(0.6126)
Competitors' Info.			0.0231	0.0165	0.0218	0.4410	0.1077	-0.4399
			(0.0124)*	(0.0151)	(0.0126)*	(0.1647)***	(0.0344)***	(0.5913)
Commerical Info.			0.0493	0.0726	0.0481	-0.2279	0.0785	0.4220
			(0.0130)***	(0.0168)***	(0.0130)***	(0.1860)	(0.0318)**	(0.5149)
Free Info.			0.0366	0.0522	0.0384	0.3424	0.1358	0.2938
			(0.0145)**	(0.0179)***	(0.0147)***	(0.1998)*	(0.0392)***	(0.5521)
Regulatory Info.			0.0180	0.0312	0.0161	0.0487	0.0337	-0.4588
			(0.0099)*	(0.0131)**	(0.0100)	(0.1455)	(0.0260)	(0.4754)
University Info.			0.0928	0.1205	0.0948	1.1069	0.2821	0.1683
			(0.0196)***	(0.0238)***	(0.0200)***	(0.2190)***	(0.0446)***	(0.5373)
Government Info.			-0.0563	-0.0634	-0.0582	-0.0604	-0.1201	0.1444
			(0.0168)***	(0.0206)***	(0.0172)***	(0.1748)	(0.0381)***	(0.5898)
Internal Info.– Self			0.0836		0.0803	0.8120	0.1879	1.4310
			(0.0133)***		(0.0129)***	(0.1673)***	(0.0278)***	(0.5330)***
Internal Info. – Group				0.0430	0.0205	0.0169	0.0579	0.0030
				(0.0132)***	(0.0101)**	(0.1306)	(0.0272)**	(0.4533)
CIS Wave	3	3	3	3	3	2	2 and 3	2 and 3
Enterprise Fixed Effects	No	No	No	No	No	No	No	Yes
Observations	4,871	4,871	4,871	4,871	4,871	1,550	6,421	202

Notes: *Patents* is the number of patents applied for over the 1998-2000 period. Each column is a different estimated specification, with each row in columns (1) through (8) reporting the marginal impacts (and robust standard errors, clustered by enterprise group) for the indicated regressor as estimated by a negative binomial model. *, **, and * * * indicate statistical significance at the 10%, 5%, and 1% levels. All specifications include additional control regressors (not reported for brevity): two-digit industry dummies; 12 regional dummies; enterprise total employment; a categorical indicator of structural change (see C); and for columns (7) and (8) a CIS Wave indicator.

echoing the finding of vertical spillovers in micro-level productivity studies. Finally, regulatory information is negative which might be expected, whereas information from competitors is also negative, which might not be expected. One possibility is that conditional on all these other sources of information enterprises learning from their competitiors might be innovation laggards. The remainder of the table explores these results further. Column 6 shows an IV estimate of column 5, instrumenting H with the industry averages derived from CIS2 set out above. The coefficient on H does not change although the precision of the estimate falls somewhat, as might be expected with IV estimation. Column 7 estimates the same regression for CIS2, where note there are many fewer observations. The overall coefficient estimates look very similar indeed with only one coefficient changing sign (that on commercial information)[14] but the precision of the estimates is reduced, in line with the smaller sample size. Column 8 then pools CIS2 and CIS3 together and returns quite precisely estimated effects, similar in magnitude to the CIS3 cross-section in column 5.[15] Finally, column 9 shows the coefficient estimates (not the marginal effects) for a fixed effects conditional logit model. The number of observations is 494; recall that this model relies on enterprises who changed from innovating to not innovating (or vice versa) which in this case is 247 enterprises (observed twice making 494 observations). Thus the number of observations is small and selected, as discussed above. Recalling that we cannot compare the magnitudes of the reported coefficients since they are not marginal effects, the following points are worth noting. Firstly, the only statistically significant variable is learning from one's own enterprise, which is strongly significant. Secondly, all the other variables are statistically insignificant at conventional levels, with the only variables to have t statistics in excess of unity are multinational parents (positive coefficient), vertical information (positive), and competitor's information (negative). Thus one possibility is that innovation and its inputs are highly serially correlated and that we simply have too few observations

[14]This might be due to this variable being slightly differently defined in the two surveys, due to changes in the survey question (see Appendix C.1.4 for details.

[15]We also comment here on the unreported regressors. The dummy on expanding startups generally has a positive coefficient, as we would expect. Many industry dummies are individually significant, and all are jointly significant. Regional dummies largely insignificant individually and jointly. Size almost always significantly positive, as we might suspect. Finally, the CIS3 wave dummies in the pooled and fixed effect specifications are negative implying a fall in ΔK in 1998-2000 relative to 1994-96. This is entirely consistent with the fall in UK TFP between the early and late 1990s documented by Basu, Fernald, Oulton and Srinivasan (2003).

of switchers to pick up statistically significant effects (the other possibility is of course that the innovation process is truly dominated by factors not measured by our regressors aside from internal information). To get some idea of this we ran a pooled regression on the 247 enterprises over the two years and found again that none of the coefficients were statistically significant, suggesting that the source of the problem is the small sample.[16]

We would not wish to rely on one measure of innovation however, and thus we turn to Table 4.5 where ΔK_i is measured as the numbers of patents the firm has applied for during the 1998-2000 period. The pattern of findings is similar to that of Table 4.4, but with some interesting differences. Regarding the similarity, firstly, the coefficient on the GE dummies falls when the information flow variables are included (compare column 3 to columns 1 and 2). Secondly, the coefficient on R&D personnel is consistently positive (although not significant in column 9). Thirdly, the information flow variables are also statistically significant, in particular the two internal flow variables. Finally, in both tables the significance levels in the fixed effects regressions are rather low. There are at least two interesting differences. First, Table 4.1 shows very substantial differences in the number of patents applied for between GE and domestic firms: MNE parents applied for on average 10.02 patents and domestics 0.10 patents. Yet the coefficients on the GE dummies in table 5 column 1 suggest differences of between 0.2 and 0.7 of a patent. Recall however that this regression includes industry dummies, which if dropped, render the GE coefficients similar to the raw GE/domestic differences in Table 4.1. This emphasises that much of the variation in patents is industry-specific. Additionally, it is interesting to note that the university information variables are highly significant which one might expect given the innovation measure is patents. The coefficient on vertical information, contrary to table 4.4, does not enter the equation in a consistent way, for one specification is significantly positive, for some insignificant and in one case is significantly negative. In column 9, we report the coefficients of the negative binomial fixed effects. The sample is very small (n=198), as expected the coefficients present the same broad patterns as in the previous columns but the standard errors

[16]Note also that we checked the robustness of the results to having chosen probit rather then logit as our preferred estimator. Unreported logit estimates of columns (1)-(8) yield very similar results to the ones presented.

have increased dramatically for most regressors except for the internal information – self variable which stays very significant.

A number of points are worth highlighting from these results. First, what is the status of our estimated coefficients given the problems of endogeneity? As in almost all studies of production functions, there is bound to be an unobserved variable, such as managerial talent, that affects both outputs and inputs. Regarding our study the following points are worth making.

First, whilst we expect omitted variable bias from omitted managerial inputs our main focus in this paper has been the omitted variable bias from omitted knowledge flow inputs, which are often unavailable in many data sets. We have, we believe, documented substantial bias from this source, which we think to be of interest.

Second, there is then of course remaining bias from unobservable managerial variables. To some extent the GE dummies capture this, since a body of evidence has documented that such firms have higher productivity controlling for all other observable inputs. Thus, the omitted variable bias to our explanatory variables arises from that part explaining differences in ΔK over and above the average effects of the status of domestic, home and affiliate MNE and exporter status. The quantitative impact of this remaining bias is unclear. A solution to it requires more data: more cross sections to control for the fixed part of it and more data to better identify exogenous variation in the regressors. Finally, we have attempted to control for this bias by instrumenting the H variables and to the extent that the information flows variables are exogenous to the firm (e.g. information from universities) bias should be less of a problem.[17] Second, although in all specifications the GE dummies are reduced by the inclusion of information flows, they typically remain statistically significant, and so contribute at least some explanatory power to the variation in ΔK_i. This then raises the question of how much of the variation in ΔK_i is explained by differences in GE status and how much by these inputs.

From these tables, we can now set out, for both ΔK measures, the proportion of the innovation advantage of MNE parents accounted for by a number of factors. For example, we find that a higher level of R&D personnel explains almost 14% of the observed within industry-region domestic multinational advantage (from column 1 of

[17]However, these information flow variables are weighted by their importance which is plausibly correlated with managerial ability.

Table 4.4, and 20% of the foreign affiliates innovative advantage.[18]. The knowledge flows explain an additional 58% of the domestic multinational advantage and 60% of the foreign affiliates advantage.[19] The figures for the Patents variables are similar, although now the number of R&D employees explains 19% of the domestic MNE lead in patenting activity and only 6% of the foreign affiliates'. Information flows explain an additional 69% of the MNE innovative advantage and almost 73% for the foreign affiliates.

4.4.3 Robustness Checks

The results in Tables 4.4 through 4.5 are robust to a number of measurement and specification choices. In particular, the general impacts of our global-engagement and information-source regressors do not change when we vary the exact H measure of firm use of innovation-producing workers: e.g., if we use the level of scientists, or the total level of graduate workers instead of R&D personnel or shares of either of these measures rather than level. Results also do not change when we vary the set of control regressors: e.g., using firm sales instead of firm employment for size, or including age.[20] We also estimated a large number of specifications interacting our global-engagement indicators with other regressors-e.g., with our measures of H to see if globally engaged firms enjoy higher marginal productivity from knowledge inputs. These interactions almost always were insignificantly different from zero.

4.5 Conclusions

In this chapter we have tried to quantify how much of the superior innovative output of globally engaged firms in the UK is due to R&D investments and how much to external knowledge flows. Our approach has been to estimate knowledge production functions on a data set of U.K. firms in both the manufacturing and service sectors for which we have detailed information on knowledge outputs, inputs, and

[18]Note that in column 1 we also control for size and structural change. These figures are calculated as: 14%=(0.2204-0.1902)/0.1902 and similarly, 20%=(0.1871-0.1496)/0.1871

[19]58%=(0.19-0.06)/0.22, and similarly for 60%.

[20]The main reason why the variable age is not included in the main specification is that for the service sector firms, this variable is censored at 1997, the first year the ARD data is available for this sector.

– importantly – flows from various knowledge stocks. We focused in particular on the hypothesis from the trade literature that globally engaged firms – either multinationals or exporters – have access to larger knowledge stocks. We found that globally engaged firms do generate more ideas than their purely domestic counterparts. This is not just because they use more knowledge inputs. Importantly, it is also because they have access to a larger knowledge stock through two main sources: their upstream and downstream contacts with suppliers and customers, and, for multinationals, their intra-firm worldwide pool of information.

These results offer an initial step in the direction recommended by Jones (2003) in his forthcoming literature survey of economic growth: examining real-world data. As such, the results suggest that future modelling needs to think harder about possible pitfalls from assuming a seamless global stock of knowledge to which all actors have easy and equal access. These results also inform the growing literature in trade on multinational firms. For example, the now-standard knowledge-capital model of multinationals is largely silent on how these firms optimally structure intra-firm knowledge sharing. In future work, we aim to apply our data to issues such as these.

Chapter 5

Innovation and productivity growth

5.1 Introduction

There is an extensive literature on innovation, investigating both its determinants and its contribution to firm performance (measured as productivity growth or as market value).

Since the seminal papers by Griliches (1979) and Griliches and Pakes (1980) a widespread approach is to frame the relationship between innovation and its determinants in a knowledge production function and the contribution of innovation to productivity growth in an output production function. The knowledge production function approach described in Griliches and Pakes (1980) assumes that the production of new knowledge depends on current and past investment in new knowledge (e.g. current and past R&D expenditures), and other factors such as knowledge flows from outside the firm.

A first order measurement problem that economists have had to face is how to measure 'new knowledge'. There are broadly two ways to approach the problem. A first approach is to use patent data to measure 'inventive output'. Although patents are a direct measure of the output of the innovation process, by no means all innovations are patented and there is great heterogeneity in the propensity to patent among firms, because of great differences in the relative importance of patenting as a barrier to imitation both between sectors and among different type of innovations.

A second stream of the literature measures additions to knowledge capital indirectly using total factor productivity growth and relates this directly to R&D stock constructed using perpetual inventory methods (see for example Hall and Mairesse (1995)). The main limitations of this approach are that productivity growth is a noisy measure of innovative/inventive output and that R&D, though typically well-codified, is only an input to the innovation process and what really matters for total factor productivity growth is the output of this process.

Both approaches use, as proxies for investments in knowledge capital stock, measures based on past and present R&D expenditure of the firm. The strengths and weaknesses of this measures are well-known; measures of R&D are reasonably well codified. However, firms, in particular small and in the service sector, might generate technological advance outside formal R&D laboratories which R&D expenditure might not capture.

A similar measurement problem arises in the attempt to capture knowledge flows or knowledge spillovers that, because of the public good aspect of knowledge, contribute to the production of innovative output. There are two approaches. One uses patent citations to measure knowledge flows (see e.g. Jaffe (1986) and Jaffe et al. (1993)). Once again, a strength of this literature is that patents and citations are well-codified. However, it is likely that patents do not measure all innovations. Furthermore, there has recently been some criticism of the use of citations.[1] A second stream of literature uses aggregate level of R&D within the firm's industry to capture horizontal knowledge spillovers, or across industries weighted using input-output tables to capture backward and forward linkages ('vertical' spillovers) (see e.g. Bernstein and Nadiri (1989); see also Griliches (1992) for a survey).

This chapter attempts to build on a third approach which tries to overcome some of the problems discussed above in the measurement of both innovative output and knowledge flows. It should be stressed at the outset that given the deep measurement problems no approach, including the one discussed here, is perfect. Therefore this approach is to be considered as a complement to those above and this analysis is

[1]The issue of concern is the noise that examiners' citations add to estimated flows of knowledge. Using newly available US patent data showing citations added by examiners, Alcácer and Gittelman find that examiners add 40 per cent of all citations and two-thirds of citations on the average patent are inserted by examiners. Furthermore, examiners' citations differ systematically from inventors' citations. This may bias estimates of the parameters of interest.

very much of an exploratory exercise into whether the new data used might be helpful in confirming or adding to the insights the current literature has generated. This approach endeavors to model the links between innovation inputs, external knowledge flows, innovation outputs and productivity growth using new information from firm level innovation surveys.

As in chapter 4 the data is based on the UK Community Innovation Survey (CIS), a survey carried out in EU countries in the early, mid and late 1990s[2] along the lines set out in the Oslo manual (1992). This company survey attempts to measure innovations directly by asking firms about their product and process innovations and their innovation inputs by asking about expenditure on R&D and other knowledge investments and the relative importance of various knowledge flows. Thus, the key contributions of these data is that one can estimate the knowledge production function using a different output; rather than patents, I use the proportion of sales generated by new products and the presence of process innovations. Also I use different inputs; not only R&D but all innovation expenditure (including e.g. investment in training and design activities). Of course, a host of other issues arise, such as accuracy of measurement, use of self-reported data, etc., which is why this approach is also not immune to measurement problems.

A significant limitation of the CIS questionnaire is that it has no labour productivity /TFP information on it. Thus, one cannot examine the relationship between the CIS innovation measures and productivity without linking the survey with other data sources which can provide information on productivity. The matched innovation-productivity data quantifies the performance effects of the innovation processes that the CIS describes.

This chapter implements this linking for the UK manufacturing sector. The UK CIS was carried out using the same sampling frame (the Interdepartmental Business Register, IDBR) as the one used to conduct the ABI. We have therefore obtained the raw innovation data and corresponding production data and matched them. The ABI provides a wealth of information on output, employment, material use, capital etc. Thus the matching allows me to relate productivity/TFP with innovation. To the best of my knowledge this study is the first to use this matched information for

[2]For the UK there have been three CIS surveys, CIS1 (covering the period 1991-3), CIS2 (1994-6) and CIS3 (1998-2000).

the UK.[3]

The main objectives of this chapter are the following. Firstly, since these data have not been analysed before the study carefully analyses, identifies and corrects inconsistencies in the data. Secondly, the study develops a framework that explains the different stages of the development of both product and process innovation and links them with the productivity growth of the firm. Thirdly, I apply this theoretical framework to find consistent patterns in the data.

The results show the following. Firstly, the firm's decision whether and how much to invest in innovation is positively correlated with international competition, the availability of skilled workers and with the availability of methods of protection of innovations. Secondly, internal innovation expenditure is only one of the factors associated with successful innovation. The results show that cooperation and knowledge from other firms in the enterprise group and from suppliers and customers have a positive correlation with successful innovation. However, I need to point out that when drawing conclusions from these results I am faced with data limitations: whilst firms are asked about the sources of their external knowledge they are not asked if such sources are paid for. Thus, I cannot define such sources as 'pure spillovers'. Thirdly, my results show that it is important to distinguish between product and process innovation, as well as novel and incremental (non-novel) innovations. Some of the self-reported estimates of innovation are correlated with TFP growth and some are not: in particular the negative correlation between novel process innovation and productivity growth might appear counterintuitive. This might reflect reality, since process innovations take time to feed through to productivity growth, or the fact that firms that face a decrease in demand or are going through financial difficulties are more likely to implement process and that this improvements will be reflected in increased productivity with some delay (Davis and Haltiwanger, 1990, and Nickell et al., 2001) but it might reflect the weakness of the measures used. I investigate this issue further in the chapter. I try to control for the delay in the effect for process innovation using information on the success of process innovation using self-reported information from the innovation survey. I find that process inno-

[3] Harris and Robinson (2001) has matched the UK CIS with the UK Census of production, but has not analysed the matched data. Examples of matched CIS/Census data are, for France, Crépon et al. (2000); for the Netherlands, Klomp and van Leeuwen (2001); for Sweden, Loof and Heshmati (2002) and for Finland, Leiponen (2000).

vations that firms report as being successful in improving production flexibility are correlated with positive productivity growth.

I also show that organisational and managerial change is positively correlated with productivity growth conditional on technological process and product innovations.

Finally, I show that the rate of returns to R&D are, as in previous studies, quite imprecisely estimated when the R&D sales ratio is included in a productivity growth equation. In a regression of firm reported innovation on own R&D, I find that the returns to R&D are much more precisely estimated.

The chapter is organised as follows. In section 5.2 I describe the data. Section 5.3 relates my approach to the previous literature and in particular to previous empirical studies that have used the CIS and matched Innovation-Production data. Section 5.4 sets out an organising framework. Section 5.5 reports the empirical results. Section 5.6 concludes. In the Appendix D I report more details on the data, the cleaning procedures and the definition and construction of the main variables of interest as well as additional results.

5.2 The Data

5.2.1 The ARD

The ONS Annual Respondents Database (ARD) is described in some detail in Criscuolo et al. (2003), so only a brief description is included here. The ARD consists of the micro data from the Annual Census of Production (ACOP) up to 1997 and the Annual Business Inquiry (ABI) thereafter. The micro data are the replies to the Census forms, response to which is mandatory under the 1947 Statistics of Trade Act. These forms are sent out to firms who are on the UK business register (the Inter-Departmental Business Register, IDBR) and requests information on inputs and outputs. Information is also collected on plants' industry, region, and nationality of ownership. Each unit who replies is assigned a unique identification number. Units also have another identification number corresponding to the entity that owns them (the firm) so units under common ownership share the same firm identifier.

To limit reporting burdens on businesses, the ACOP/ABI are both stratified sample surveys. All larger enterprises over a threshold number of employees are surveyed, but a sample is taken of smaller enterprises (with the sampling rules changing every so often (see Criscuolo et al., 2003 for details). These surveyed businesses form what is called the "selected" sample and they account for over 80% of total employment in manufacturing (Oulton, 1997). The rest of the units on the register are not sampled (the "non-selected" sample), and their information on industrial classification, region and employment comes from the business register. In addition to those units that were "non-selected" for the survey, some units that did not respond also have only register data available. Register employment information comes from separate inquiries and may, for firms below 10 employees, be imputed from turnover data (Perry, 1995).

In my analysis, the main concerns are related to the level of aggregation. Surveys are conducted at the "reporting unit" level. This may be an individual "local unit", where a "local unit" (in the manufacturing survey) is a production facility at a single mailing address, which corresponds to a production unit or plant (in retailing for example it would be a shop). However, in multi-plant or multi local unit firms, the "reporting unit" may be a group of local units, where the grouping is agreed by the ONS and the firm (along similar product lines for example).

In the measurement of productivity growth problems may arise when "reporting units" decide to change over time the number of local units they report on. To minimise measurement error I use a cleaned[4] dataset that excludes all unrealistic growth rates for output and inputs of the production process. Secondly, given the "selected" vs. "non-selected" structure of the data, the ARD panel is unbalanced panel and with gaps, i.e. reporting units productivity measures (e.g. value added and material inputs) are only available for the years when the reporting units are in the "selected sample". In Appendix D.3 I describe in detail how I constructed the growth measures to account for this. Moreover, I concentrated my attention to calculating growth variables for the latter half of the '90s, since in 1993 and 1994, a complete recoding of local, reporting and firm identification numbers was undertaken.

Additional issues arise when matching the ARD to other datasets, such as the

[4]Details of the cleaning procedure are given in the Appendix D.

Community Innovation Survey (CIS). We will discuss these after having described the CIS.

5.2.2 The Community innovation Survey

The Community Innovation Survey (CIS) is a voluntary postal survey carried out by ONS on behalf of the DTI. Eurostat proposed an initial questionnaire and the DTI added questions. The CIS began in 1993 (CIS1) and was repeated in 1997 (CIS2) and 2001 (CIS3). As the response to the first CIS survey was poor, the CIS2 is the first survey I can use to conduct analysis. Each time a stratified sample of firms with more than 10 employees is drawn from the Inter-Departmental Business Register (IDBR) by industry, region and size. The survey covers both the production and the service sectors. Fieldwork for the second Community Innovation Survey took place between August 1997 and March 1998 and firms were asked to complete data referring to the period 1994 to 1996. At the time of selection, 5,892 were sampled and 2,339 responded (Table 1, column 1, row 1 and 2; accounting for bankruptcy, this was a response rate of 43.2%. Manufacturers and service sector companies were sent very slightly different questionnaires ; replies and response rates were 1,596 and 743, 41% and 37% respectively . The Third Community Innovation Survey (CIS 3) was in the field twice. The first wave sampled 13,340 enterpises, the second top-up covered 6,285 to make the sample representative at the regional level. The CIS 3 covers the period 1998-2000. Of the total 19,625 enterprises to which the survey was sent, 8,172 responded, achieving a response rate of 42%. Table C.1 sets out the details the composition of the innovation surveys.

Since the CIS is a voluntary and postal survey, one of the main problems for this sort of surveys is the risk of low-response and thus of non-response bias. To boost response, enterprises are sent the survey, posted a reminder, posted a second reminder (with the survey again) and finally telephoned. Although data custodians have reported no bias for both CIS2 and CIS3, when looking at the characteristics of both respondents and non-respondents I find (in unreported analysis) that in both CIS2 and CIS3 non-respondents are on average significantly larger than respondents, both in terms of turnover and employment.

A second issue is that the survey was conducted at the enterprise level; where enterprise is defined in the questionnaire as *"the smallest combinations of legal units which have a certain degree of autonomy within an enterprise group"*. This corresponds to the "reporting unit" level at which the ABI is carried out thus facilitating matching. However, there might be discrepancies between the two surveys due to different people within the firm responding to either survey and to the CIS responses being retrospective.[5]

The third issue is that the answers to a survey are necessarily subjective. The essential idea of the survey is to try to get enterprises to report separately technological change/innovations as opposed to organisational innovations. In turn, technological innovations are split into process and product innovations.[6] Since companies are asked about products or processes that are"technologically new" there is obvious scope for differences in interpretation of "technological" and "new". The questionnaire does however give extensive guidance on both these terms, but there is always the problem of misinterpretation or indeed reporting yes to all questions for fear of a company being seen as in some way backward. All this introduces measurement error into the level of innovations, biasing us against finding a significant relation between productivity growth and innovations if firms are randomly mis-reporting or biasing down the expected relation if firms report positively innovations when they

[5]We check the robustness of my result to this issue in two ways: firstly I estimate productivity growth regressions only on the subset of single firms-plants; secondly I only keep those firms for which the ratio of the turnover reported in CIS to the turnover in ABI either for 1998 or 2000 is within the [0.5,1.5] range.

[6]The questions concerning product and process innovation are as follows. Regarding product innovation, the survey reads *"For this survey product innovation covers both goods and services introduced to the market which are either new or significantly improved with respect to fundamental characteristics. The innovation should be based on the results of new technological developments, new combinations of existing technology or utilisation of other knowledge by your firm. For examples of product innovations see inside front cover. We are interested in products new to your enterprise - even if already on the market - as well as those that are new to your market."* And the question is: *"During the three year period 1998-2000, did your enterprise introduce any technologically new or significantly improved products (goods or services) which were new to your firm?"*. Similarly for process innovation, *"For this survey process innovation is the use of new or significantly improved technology for production or the supply of goods and services. Purely organisational or managerial changes should not be included. For example of process innovations see inside front cover. We are interested in processes new to your enterprise - even if already in use in your industry - as well as those that are new to your industry."* and the question: *"During the three year period 1998-2000, did your enterprise introduce any new or significantly improved processes for producing or supplying products (goods or services) which were new to your firm?"*. Reported examples of process innovations - derived from real examples from previous surveys - are: Linking of Computer Aided Design station to parts suppliers; Introduction of Electronic Point of Sale equipment in Garden Centre; Digitising of pre-press in printing house; Robotised welding

are not actually innovating.[7] Companies are asked to describe their most important product or process. The response rates are not high (about 30%) but a casual perusal of the responses indicated that, except a hand full of respondents, enterprises were able to identify technological innovations.

Fourth, the survey asks for innovation in the period 1998-2000 (1994-96 for CIS2), but innovation expenditure in 2000 (in 1996 for CIS2). If innovation expenditure is highly serially correlated this should not be too much of a problem, but I acknowledge this is a limitation, especially when estimating the knowledge production function.

In the next section, I describe the issues related to the matching of innovation and production data.

5.2.3 Matching CIS and ARD

The Office for National Statistics (ONS) maintains a register of businesses designed to capture the universe of activity. Before 1994 this was for production activity, but since 1994 it has covered services as well. The pre-1994 register was drawn from a variety of sources including historical records, tax returns and other surveys. Since 1994 it is based on the Interdepartmental Business Register (IDBR).

Since both the Community Innovation Survey and the Annual Business Inquiry use as sampling frame the IDBR, matching of the two datasets is based on the common 'reporting unit' identifiers. However, in the matching process care must be taken because of inconsistencies across the two surveys.

Businesses are asked to provide reporting unit level information for the CIS and I therefore matched at the reporting unit level. However, for multi-plant establishments the "reporting unit" level in the ARD does not always seem to perfectly match the reporting unit level in the CIS survey, according to variables present in both surveys such as employment and turnover. Although there is no easy solution to these problems, I identified those reporting units for which differences across survey suggest differences ion levels of reporting information and checked the robustness

[7] An alternative is that firms are always too optimistic or pessimistic e.g. they systematically over- or under- report both innovations and inputs to innovations (R&D, knowledge flows etc.) leading to a spurious correlation between the two, however since it is likely that different people within the firm answer the two questionnaires and that the forms are distributed at different point in time, this problem seems less likely to be a major issue in my case.

of my results to the inclusion of these observations.[8]

The second source of discrepancy lies in the industrial classification. In those cases (less than 100) where there was a discrepancy between the industrial classification in the Innovation survey and that of the ARD, I use the classification from the ARD.[9] Moreover, since the innovation survey is the same for both production and service sectors, I decided to include in the sample the few enterprises that were in the manufacturing sector according to the ARD but in the service sector according to the CIS.[10]

In the next section I describe the features of the CIS sample and the matched CIS-ARD sample that I use for the empirical analysis.

5.2.4 Some Features of the Data

Table 5.1 reports characteristics of both the CIS3 sample and the CIS3-ARD matched sample.

In both panels, looking at the top row, the median firm in CIS3 does no patenting, although the mean firm in the CIS3 sample did apply for 1 patent in the 1998/00 period and in the CIS3-ARD matched sample did apply for 3 patents. The second row shows the median firm in CIS3 spends zero percent of its sales on R&D, with again slightly a higher mean figure of 0.6% (0.7% in the bottom panel). Both these results reflect the well-known skewness in patents and R&D: Bloom and van Reenen (2002), report that the 12 largest UK firms account for 72% of patenting and 80% of R&D expenditure.

Row 3 to row 9 widen the scope of innovation data. Firstly, row 3 reports the total spending in innovation, i.e. inside and outside R&D laboratories (for acquisition of external knowledge, design, training, marketing and machinery). Here, the median firm spends 0.3% (0.7% in the bottom panel) of its sales on innovation and the mean

[8]Since the CIS3 is asked retrospectively and the persons answering the questionnaire are likely to be different from those responsible for answering the ABI, I do not expect the values of turnover and employment reported to be exactly the same in the two surveys. We decided to consider problematic observations those for which the ratio of employment in 2000 in CIS3 and on employment in 2000 from the ARD is either smaller than 0.5 or larger than 1.5.

[9]In unreported regression results I checked the robustness of my result to this choice. The results were virtually unchanged.

[10]This choice was also supported from the direct information from the enterprises available in CIS3 ("please briefly describe your enterprise's main product "), which was available for some of these reporting units

Table 5.1: Summary of innovation measures, CIS3 and CIS3-ARD matched sample

CIS3 sample

		medians	means	sd
1	Number of patents applications	0	1.215	*(8.242)*
2	R&D spending (% of turnover 2000)	0	0.006	*(0.032)*
3	Innovation expenditure (% of turnover 2000)	0.003	0.027	*(0.070)*
4	Novel process (0/1)	0	0.083	*(0.276)*
5	Process Innovation (0/1)	0	0.241	*(0.428)*
6	Novel product (0/1)	0	0.132	*(0.339)*
7	Product Innovation (0/1)	0	0.278	*(0.448)*
8	%Turnover new and improved products	0	0.080	*(0.191)*
9	% Turnover novel products	0	0.022	*(0.095)*
	matched ARD-CIS3 sample			
1	Number of patents applications	0	2.770	*(13.220)*
2	R&D spending (% of turnover 2000)	0	0.007	*(0.021)*
3	Innovation expenditure (% of turnover 2000)	0.007	0.026	*(0.048)*
4	Novel process (0/1)	0	0.121	*(0.327)*
5	Process Innovation (0/1)	0	0.346	*(0.476)*
6	Novel product (0/1)	0	0.191	*(0.393)*
7	Product Innovation (0/1)	0	0.386	*(0.487)*
8	%Turnover new and improved products	0	0.095	*(0.196)*
9	% Turnover novel products	0	0.029	*(0.107)*

Notes: Reported statistics are unweighted medians, means and standard deviations. In panel 1, the CIS3 sample used contains 2687 observations. The matched CIS3-ARD sample used in panel 2 contains 708 observations. Both samples only include manufacturing firms. For a definition of the variables I refer to the appendix.

firm 2.7% (2.6% in the bottom panel). The fifth to ninth rows of the table give some evidence on whether the firm reports any process or product innovation. Although the median firm still reports zero innovation using these innovation indicators, on average 24.1% (row 5, top panel) and 27.8% (row 8, top panel) of firms have process or product innovated. Thus the distribution is much less skewed and the CIS3 seems to be capturing something broader than R&D or patents. As well as just data on process and product innovation, the CIS3 also asks respondents to differentiate between product and process innovation that is "new and improved", or"novel", the latter being defined as new to the market (product innovation) and new to the industry (process innovation). Row 4 and 6 in the table show, not surprisingly, that fewer firms engage in novel innovation, both product or process. Finally the table shows the share of innovation expenditure in total output, which although small, is larger than just R&D expenditure and less skewed. Figures in the top and bottom panel provide the same qualitative picture, which is also very similar in quantitative terms. This gives us reassurance regarding the representativeness of the matched sample relative to the whole CIS3.

CIS3 adds information on the internal and external sources of knowledge.[11] As described in detail in the appendix, we distinguish among various sources of innovation. Table 5.2 reports the importance of these sources of information for firms with below and above median innovation expenditure. Two interesting facts emerge. Firstly, looking down the columns gives an indication of what sources of information are more highly rated. Internal and vertical information is highly rated by both groups of firms as is free and regulatory information. Secondly, firms with innovation expenditure above the median i.e. who are investing more in generating innovations also report higher importance of other knowledge flows. For example, the importance of internal and vertical knowledge flows triples in firms with above median innovation expenditure. This suggests that returns to innovation expenditure estimated in studies that cannot account for the role of external knowledge flows might be affected by a (upward) omitted variable bias.

[11] I would like to stress that our measure of external knowledge should be viewed as wide measure of knowledge flows, that include two different mechanisms of transmission: 'pure knowledge spillovers' that do not entail a market transaction and knowledge acquisition for which the firm is paying a price. Given the nature of the question, however, I think our measure does not encompass 'rent spillovers', defined as pecuniary gains because of improved or cheaper inputs.

Table 5.2: Information sources for firms with below median and above median innovation expenditure, CIS3 sample

	information sources	below median	above median
1	internal	0.176	0.663
		(0.315)	*(0.351)*
2	from the group	0.093	0.323
		(0.232)	*(0.362)*
3	vertical	0.222	0.683
		(0.336)	*(0.307)*
4	competitors	0.119	0.368
		(0.236)	*(0.312)*
5	commercial	0.080	0.296
		(0.196)	*(0.310)*
6	free	0.175	0.513
		(0.287)	*(0.311)*
7	regulation	0.195	0.558
		(0.320)	*(0.340)*
8	university	0.058	0.210
		(0.174)	*(0.282)*
9	government	0.048	0.171
		(0.152)	*(0.255)*

Notes: Reported statistics are unweighted means with standard deviations in parentheses. means. Column 1 for a sample of 1,344 observations and column 2 for a sample of 1,343 observation. The sources of information vary between 0 and 1. The definition of the sources of information is as follows: row 1 refers to information from within the enterprise; row 2 'group' refers to sources with other enterprises within the enterprise group; row 3, 'vertical' sources from clients, customers, suppliers; row 4 from competitors; row 5 'commercial' to information from consultancy enterprises, research association or commercial R&D laboratories; row 6 'free' from professional conferences, meetings and journals; row 7 'regulation' from health and safety and environmental regulations and from product standards; row 8 from universities; row 9 'government' from government institutes; training and enterprise councils; Business links.

Table 5.3: Relative TFP, market share and productivity growth for non-innovators, incremental and novel process and product innovators

Process Innovation	none	new to firm	new to industry
Initial relative TFP	0.014	0.015	0.045
	(0.203)	*(0.209)*	*(0.204)*
Initial market share	0.026	0.026	0.031
	(0.069)	*(0.053)*	*(0.065)*
LP growth (1997-2001)	0.022	0.045	0.011
	(0.178)	*(0.141)*	*(0.168)*
TFP growth (1997-2001)	0.007	0.011	-0.001
	(0.065)	*(0.072)*	*(0.068)*
Product Innovation	**none**	**new to firm**	**new to the market**
Initial relative TFP	0.004	0.016	0.066
	(0.205)	*(0.188)*	*(0.212)*
Initial market share	0.022	0.038	0.030
	(0.047)	*(0.101)*	*(0.065)*
LP growth (1997-2001)	0.020	0.033	0.038
	(0.174)	*(0.147)*	*(0.175)*
TFP growth (1997-2001)	0.005	0.008	0.013
	(0.065)	*(0.052)*	*(0.086)*

Notes: Reported statistics are unweighted means with standard deviations in brackets. Number of observation is 678 for productivity levels and 708 for productivity growth. Of these 708, 458 did not process innovate, 161 did only incremental process innovation and 89 introduced a novel process. The figures for product innovation are: 434 did not product innovate, 142 introduced a product new to the firm and 132 introduced a product new to the industry.

One final question of interest relates to whether firms spend nothing on innovation but can still successfully innovate because they can get information for free. I therefore computed how many firms report having innovated with no reported innovation expenditure. In the raw data some firms report unquantified spending, so I treated this as a positive expenditure; in the whole manufacturing sector (i.e. including tobacco and nuclear fuel) including Northern Ireland, there were 29 firms who report having innovated with no reported expenditure. Note that this is an upper bound on the true number since the questionnaire asks for innovations from 1998-2000 but innovation expenditure in 2000. On a sample of 3,440 firms this is a bit under 0.84% of firms. Thus I decided to treat these observations as outliers and drop them from the analysis.

Table 5.3 sets out the productivity levels, market share and productivity (labour productivity and TFP) growth of innovating and non-innovating firms. Looking at the top panel for process innovators, the group of firms who do no process innovation have on average a relative TFP of 1.4% above the industry median level, those reporting non-novel process innovation have a similar mean level of 1.5%. In the third column we report the relative TFP of novel innovators: they are very much the best firms, in terms of relative TFP with an average level of 4.5%, both economically and statistically significant higher than the firms in the previous two columns. The figures for market share follow a similar pattern, although the lead of novel process innovators is not as strong. The picture is reversed when we look at productivity growth: here the novel process innovators are the worst performs, with negative TFP growth. The data for product innovation shows a similar pattern in terms of initial relative TFP, with the novel innovators being the best firms and the 'imitators'[12] better than the firms who do nothing. In terms of market share there is no significance difference between novel and non-novel product innovators. Regarding productivity growth, the picture is the opposite of what we saw in the top panel: the novel product innovators are also the enterprises with the highest (labour and TFP) growth.

5.3 How do we fit in with the previous literature

The main difference between this chapter and much of the previous literature is that changes in knowledge stocks are typically assumed to be either not measured, or measured by variables such as R&D (e.g. Klette (1996)) and/or patents.

Many studies use, as a proxy for innovation output, R&D intensity, measured either as percentage of expenditure on R&D on total sales or as the proportion of R&D employees. The main advantages of using R&D as innovation measure are that the definition of intra and extramural R&D is well codified and internationally harmonised in the Frascati manual and many subclassifications of R&D are avail-

[12]We define imitators those who did not answer yes to the following question: "During the three year period, did your enterprise introduce any new or significantly improved products which were also new to your enterprise's market?" But did answer yes to the following question: "Did your enterprise introduce any technologically new or significantly improved products (goods or services) which were new to your firm?" I also call them non-novel innovators.

able (product vs process; development vs applied; intra vs extramural). Long time series are available both at the macro and micro level in many countries. One of the main criticisms in the literature is that R&D is an input to innovation, whose outcome is extremely uncertain. Secondly, R&D is only one of the inputs, indeed R&D measures do not account for technological activities generated outside R&D laboratories (e.g. in Design offices and Production engineering departments). This means that it captures very imperfectly the development of technology in small firms and in the service sector and underestimates process innovation and the development of (mainly software) technology related to information processing. Thirdly, for large multinational corporations reported R&D in one country might not reflect the actual changes in knowledge that the firm is experiencing. Finally, some see as a drawback that R&D projects differ greatly in their economic value (Freeman, 1982).

A different approach is to use patent data as a measure of the output of the innovation process. The advantages are again the large availability of data, which is publicly (and electronically) available, and the long time-series dimension of patent information. However, this innovation measure has been criticised because both patents application and granting are not exogenous. There are major intersectoral differences in the relative importance of patenting in acting as a barrier to imitation, and thus different incentives to use patents as protection methods. This implies that patenting rates by sectors will be negatively correlated with imitation costs in that sector. Major differences exist also amongst countries in procedures and criteria for granting patents. Finally, some see as a drawback that patents differ greatly in their economic value (Schankermann and Pakes, 1986). To overcome this latter limitation recent studies have also developed methods to rank patents according to their economic relevance using forward citations (Hall et al., 2001), but also this approach is not free from criticisms.

Both patents and R&D expenditure suffer a drawback: the distribution of both patenting and R&D activity is highly skewed. Thus, firms with positive R&D spending or with some patenting activity are likely to represent a very small percentage of the whole population, thus making estimation of their relationship highly dependent on few observations. Also, studies that match performance data with R&D or patent data have two drawbacks. Firstly, they cannot estimate all the stages of the process: R&D - productivity studies cannot estimate the knowledge production function; patents-productivity studies can only estimate the last stage of the model, i.e. the innovation productivity growth relationship. Secondly, studies that use both R&D and patents data are only able to measure part of innovation expenditure in the case of R&D and part of changes in knowledge stock in the case of patents, since there are other expenditures on innovation besides R&D and not all innovations are patented.

The CIS survey attempts to develop a wider definition of innovation expenditure as well as new indicators of innovation outputs. On the input side, the CIS questions cover a wider range of input into the innovation process, both as quantitative measures (R&D, machinery, training and design expenditure) and as qualitative variables (importance and nature of information flows, cooperation agreements). On the ouput side, the main strength of the CIS is to attempt to measure innovation outputs directly as new or improved product introduced on the market and innovative process implemented in the firm. It also attempts to measure innovation "height" (Duguet, 2004), distinguishing between innovations new to the market (that we define novel innovation) and new to the firm (incremental or imitative innovations) and, for product innovations (both novel and incremental), its success, using a weighted measures of innovation sales in firm's total turnover. For process innovation, to measure success, we can use additional qualitative information on the impact of process innovation on improving production flexibility.[13]

Innovation measures derived from the CIS, however, are also not free of flaws. Firstly, the CIS is a retrospective self-reporting survey covering a three year period, so that measurement error, due to "rough guesses" (in particular for quantitative variables e.g. the sales share innovation measure or the innovation expenditure variables) or subjective interpretation (especially for qualitative variables e.g. importance of information flows, effect of innovation) is likely to be an important issue. Also, a possible criticism is that expenditure in innovation, as any other investment might be lumpy[14] and the sales weighted measures are affected by both the business and firm life cycle. Moreover, the CIS is affected by a timing issue: the questionnaire

[13]Other effects include reduction of labour and material/energy costs, and increasing capacity. We concentrate on the effects on production flexibility because we believe that they are the ones that will show up in TFP growth analysis, since the other effects will be already incorporated in the material and labour variables.

[14]This is likely to be more of a problem for expenditure in machinery and equipment, rather than for other type of innovation expenditure that according to previous evidence are quite sticky.

asks for innovation introduced over a three year period, but then it asks quantitative information on the innovation inputs only for the last of the three years; similarly it asks for the distribution of turnover between new, improved and unchanged products only for the year 2000. Finally, a general issue with CIS itself: the UK version of the questionnaire is about 14 pages long, thus relative response's quality across questions might be affected by where the question is in the survey form.

The CIS itself has no performance data and so analysis conducted using purely information from the Community Innovation Survey cannot investigate the relationship between innovation and productivity growth. Recently, a new strand of the literature has developed full structural models of the innovation process and the relationship between innovation and productivity using direct measures of innovative output from CIS type surveys matched with production data. The first to develop such a model were Crépon et al. (2000), from now on CDM, that use the French Community Innovation Survey. Different versions of their model have been applied on data from other countries: Nordic Countries (Loof and Heshmati, 2002), Chile (Benavente, 2004) and China (Jefferson et al., 2004). Klomp and van Leeuwen (2001), from now on KvL, use an alternative model to analyse matched CIS - census of production data for the Netherlands. I, therefore, discuss in more detail the CDM and the KvL models.

CDM estimate the link between R&D, innovation output and labour productivity as a system of simultaneous equations with a recursive structure using the first CIS for France. The first equation of the system is an R&D investment equation, the second is a knowledge production function, while the third is a value-added productivity equation. CDM estimate this system using the Asymptotic Least Square method (ASL). The estimation is restricted to successful innovators, and thus the R&D investment equation is estimated using a generalized tobit specification. This choice is likely to be dictated by the structure of French version of the CIS1, which has a filter question at the beginning of the form which determines whether firms answer the rest of the survey.[15] Using only firms with positive R&D expenditure likely introduces a problem of selection, since R&D expenditure only covers formal innovation activity, smaller firms who conduct their innovative activity more informally might have zero R&D activity but still spend on innovation.

[15]In the appendix they show the robustness of their results to this choice.

CDM have two versions of the knowledge production function depending on whether innovation output is measured by the proportion of sales due to new and improved products or by patents. The Cobb-Douglas productivity equation estimated in CDM has as left hand side variable the level of labour productivity. Indeed that the CDM study does not study the relationship between innovation and productivity growth. Finally, the identifying restrictions are for the innovation expenditure equation market share and diversification, and, for the innovation output equation technology push and demand pull dummies, categorical variables based on whether innovation are determined by *'technology specific dynamics'* or *'through the impetus given by the market'*, respectively.

KvL estimate a system of simultenous equation using the Second CIS for the Netherlands. Differently from CDM, KvL look at the effect of innovation on output growth, and rather than using a production function framework, they estimate the effect of innovation on sales and employment growth. As input into the innovation production function they use the total innovation expenditure rather than just R&D. This is likely to improve on the selection bias introduced in the CDM model from including in the analysis only firms with positive R&D expenditure. In the KvL model, the dependent variable in the innovation production function is again product innovation, but measured as the log-odds ratio of the share of innovative sales. As noted by Wooldridge (2002), however, the use of the log-odds transformation has two main disadvantages. First, the choice of the adjustments for the boundary values 0 and 1 is necessarily subjective; secondly the interpretation of the estimated coefficient is not straightforward without making any further assumptions. An additional difference relative to CDM, consists in the relevance given to process innovation, that was absent from the CDM model. KvL include process innovation as an additional control both in the product innovation function and directly in the performance growth equation. As in the CDM model, KvL allow for the endogeneity of both input and output of the innovation process. As instruments for estimation they use for innovation expenditure exogenous financial resources, i.e. cash-flow sales ratio and innovation subsidies; a dummy for R&D laboratories, cooperation and two indices of information sources, 'science' based, and 'other' sources, including suppliers, customers, journals and fairs and exhibitions, calculated using factor component analysis. The main effect of controlling for endogeneity and selection is to boost hugely the coefficient on innovation expenditure in the Innovation equation and the effect of product innovation in the productivity growth equation.

The analysis in this chapter differs from these studies in that it models the relationship between innovation and productivity *growth* rather than productivity *levels* and it does so by using a gross output productivity equation rather than a value-added one. Regarding the output production function specification, I also allow for non constant returns to scales and imperfect competition, following the approach suggested by Klette and Klette and Griliches. In the specification of the innovation production function I look at a broader definition of innovation expenditure that includes more than R&D intensity. Concerning the methodology I estimate the innovation investment and innovation output equations simultaneously using a two step limited information maximum likelihood method, but I estimate separately the productivity growth equation and check the robustness of the result to allowing the innovations variables to be endogenous. Also, I explicitly model a knowledge production function where the dependent variable is process innovation.

5.4 Estimating framework and Econometric Model

5.4.1 The productivity growth equation

I assume that there is a Cobb Douglas output production function which relates physical output Y to a given state of knowledge capital K, and real physical non-capital inputs, material (M) and labour inputs (L), X_j for $j = L, M$, and physical capital input C. Thus, the production function in plant i at time t is:

$$Y_{it} = Ae^{\lambda t + e_{it}} K_{it}^{\alpha} C_{it}^{\beta} \prod_{j=L,M} X_{jit}^{\gamma_j} \tag{5.1}$$

where A is an efficiency parameter and λ measures the rate of disembodied technical change.

As has been done extensively in the literature (see Mairesse and Sassenou, 1991, and Griliches, 1998) I take first differences of the log of equation 5.1 to obtain:

$$\Delta y_{it} = \lambda + \alpha \Delta k_{it} + \beta \Delta c_{it} + \sum_{j=L,M} \gamma_j \Delta x_{jit} \tag{5.2}$$

where $\alpha = \frac{dY}{dK} \cdot \frac{K}{Y}$ is the elasticity of physical output to knowledge capital. Thus:

$$\alpha \Delta k_{it} = \frac{dY}{dK}\frac{\Delta K}{Y}\frac{\Delta K}{K} = \rho \frac{\Delta K}{Y}_{it}$$

Previous papers have assumed that knowledge capital can be calculated using a perpetual inventory method, so that $\Delta K_t = R_t - \delta K_{t-1}$. Furthermore, assuming δ sufficiently small, one can include the ratio of net investment in R&D to total output in equation 5.2 to estimate the rate of return to research expenditures, ρ.

So that the estimating equation becomes:

$$\Delta y_{it} = \lambda + \rho(\frac{R}{Y})_{it} + \beta \Delta c_{it} + \sum_{j=L,M} \gamma_j \Delta x_{jit} \tag{5.3}$$

This simplification comes at a cost (Mairesse and Sassenou, 1991), since I can only estimate the net returns to R&D, and it is not clear how net and gross returns relate to each other. [16] One must also account for the fact that the level of knowledge of firm i depends on own R&D investment and, given the public good nature of knowledge, on the knowledge stocks of other firms and institutions that it can access. A major problem of measurement in the literature is how to determine what knowledge is accessible to the firm[17] and much effort has gone in devising methods of capturing the accessibility, or distance, of this external knowledge.

As noted in the literature, however, R&D is an investment in knowledge capital, whose results are not directly observable, and what matters for productivity growth is the output of this investment. As noted in Griliches (1998):

> the lack of direct measures of research and development output introduces an inescapable layer of inexactitude and randomness into my formulation.

Only if direct measure of innovation output are available it is possible to solve this issue. The Community Innovation Survey (CIS) provides such information and

[16] Alternatively one needs to assume that δ the depreciation rate of knowledge is nihil, to estimate a gross rate of return.

[17] Following Griliches (1979) i is possible to include the effects of spillover effects in a model such as 5.1 by adding a term K_{a_i}, so that the model becomes $Y_{it} = Ae^{\lambda t + e_{it}} K_{it}^{\alpha} K_{a_{it}}^{\mu} C_{it}^{\beta} \prod_{j=L,M} X_{jit}^{\gamma_j}$ where $K_{ai} = \sum_j w_{ij} K_j$ is a weighted measure of the knowledge that firm i access from source j, where the weights depend on some measure of distance between firm i and source j.

studies such as Crépon et al. (2000) and Klomp and van Leeuwen (2001) use it in structural models to estimate the contribution of innovation to productivity (Crépon et al., 2000) and to performance growth (Klomp and van Leeuwen, 2001).

In this chapter I assume that changes in the knowledge capital stock are measured by reported innovations and investigate whether there is a link between such innovations measures and (total factor) productivity growth. Our data distinguishes between product and process innovation.

As Hulten (2000) remarks, changes in TFP, all else well-measured, should be process innovations. How do product innovations enter the picture? As shown by Klette (1996) and Klette and Griliches (1996) since the γ_j are unobservable, the first order conditions for the choice of input X_j is

$$W_j = P_i \frac{\partial Y_i}{\partial X_j} \left[\frac{1}{\mu} \right]$$

where μ is the mark-up of firm-specific prices, P_i, over marginal cost. This implies that

$$\gamma_j = s_j \mu$$

where s is the share of costs of input j in output. Since P_i is unobservable, in order to proceed, one can assume that the demand curve facing the firm is:

$$\frac{Y_i}{Y_I} = D_i^{1/(\mu-1)} \left(\frac{P_i}{P_I} \right)^{-\mu/(\mu-1)} \left(\frac{K_i}{K_I} \right)^{\zeta/(\mu-1)} \tag{5.4}$$

where I am assuming that knowledge capital affects demand through improved product quality. D_i scales the share of industry output earned by the firm at a given relative price. $\frac{\zeta}{\mu-1} = \xi$ is the elasticity of demand in respect to firm's relative product quality and ζ is a parameter that measures the sensitivity of demand to quality. Indeed, each producer can gain market power for her products, depending on the elasticity of substitution between differentiated goods $\eta = \frac{\mu}{1-\mu}$, the number of firms operating in the market and the sensitivity of demand to product quality. Since I do not have firm-specific deflators for output, I cannot measure $y_i = r_i - p_i$

where r_i is log plant revenue, but rather:

$$\mathrm{r_i} - p_I = y_i + p_i - p_I \tag{5.5}$$

where small letters denote logarithms. Substituting equation 5.4 in equation 5.5 and adjusting, I can write

$$r_i - p_I = y_i \frac{1}{\mu} + k_i \xi + d_i \frac{1}{\mu} + y_I \frac{\mu - 1}{\mu} \tag{5.6}$$

where the left hand side is the output I can observe, that is sales deflated using industry level prices. Taking logs of 5.1 and substituting into 5.6 gives:

$$r_i - p_I - \sum_{j=M,L} s_j x_j = \frac{\beta}{\mu} c_i + \frac{\zeta + \alpha}{\mu} k_i + \frac{1}{\mu} d_i + \frac{\mu - 1}{\mu} y_I + \varepsilon_i \tag{5.7}$$

Time differencing gives:

$$\Delta \ln TFP_{iI} = \left(1 - \frac{\beta}{\mu}\right) \Delta c_i + \frac{\zeta + \alpha}{\mu} \Delta k_i + \frac{1}{\mu} \Delta d_i + \frac{\mu - 1}{\mu} (\Delta y_I) + \Delta \varepsilon_i \tag{5.8}$$

where

$$\Delta \ln TFP_{iI} = \Delta (r_i - p_I) - \sum_{j=L,M} \bar{s}_{ji} \Delta x_{ji} - \bar{s}_{ci} \Delta c_i$$

the bar over the s denotes the time average share.[18] In equation 5.8, the left hand side is close to conventional TFP, in that it subtracts share-weighted inputs from deflated output. It is written $\Delta \ln TFP_{iI}$ to denote the fact that output is deflated by industry level price deflator, P_I, since firm level prices P_i are unavailable. Secondly, the inclusion of Δc_i on the right-hand side allows for non-constant returns to scale and imperfect competition. Thus, $\Delta \ln TFP_{iI}$ is due to Δk_i, thanks to its effects both on decreasing costs and on increasing demand through improved product quality, Δd_i, changes in the demand shifter, plus any effects due to expansion of the industry Δy_I. In the empirical analysis we can actually model separately the effect of Δk_i on demand, as product innovations, and the effect of Δk_i on the efficiency of production inputs as process innovations. Thus, the empirical equation becomes:

[18]Note that this ignores changes in μ. This is probably one of the biggest limitations of this approach, since innovative behavious is very much likely to chage μ over time.

$$\Delta \ln TFP_{iI} = \delta_0 + \delta_1 \Delta c_i + \delta_2 PROCESS_{INNOVATION} + \delta_3 PRODUCT_{INNOVATION} + \delta_4 \Delta y_I + v_i \tag{5.9}$$

where I expect $\delta_2 = \frac{\alpha}{\mu} > 0$ and $\delta_3 = \frac{\zeta}{\mu} > 0$.

The impact of innovation might depend on the 'height' of innovations[19] and the data at hand provides different heights of process and product innovations which might have different effects on $\Delta \ln TFP_{iI}$. Firms are asked if innovations are new to the market/industry or new to the firm. I take this as a measure of whether firms are novel innovators (i.e. an innovation new to the market/industry) or innovation imitators (i.e. an innovation new to the firm but new the market/industry). Thus I estimate:

$$\Delta \ln TFP_{iI} = \delta_0 + \delta_1 \Delta c_i + \delta_{21} Process_{novel} + \delta_{22} Process_{imitate} + \delta_{31} Product_{novel} + \delta_{32} Product_{imitate} + \delta_4 \Delta y_I + u_i \tag{5.10}$$

In estimating equation 5.10 I face a timing issue. The data for the innovation variables refer to any innovation between the three year period 1998 and 2000. This leads to a number of different possible dates for the TFP measure. If innovations take time, one might want to use post-2000 data, but this might introduce additional measurement error and attenuate the true effect of innovations.[20] If there is measurement error in the production variables used to calculate TFP, one might want to average over a number of pre and post years. Finally, adding extra years in the calculation of annualised growth rate means more chance that firms who had missing TFP growth information due to sampling are now included into the sample, boosting sample size, but in a selective way since smaller firms are those

[19]see also (Duguet, 2004) for a similar argument, but without distinguishing between product and process innovation

[20]Especially if innovations reported in the survey had been in place since 1998. Also, while the existence of adjustment costs might explain the lagged effect of process innovation, it is not clear that the effect of 'realised' product innovation might have a lagged effect on productivity, rather, especially in industries that are highly competitive or have low appropriability levels, the demand lead due to novel product innovation is quickly eroded by imitators

who typically join and leave the selected sample. In the empirical analysis I have experimented with different timing in the calculation of the TFP growth measure and the results do not change according to the timing used.[21]

In the empirical analysis I also include dummies that identify the years when the firm is observed. This should at least partly account for measurement problems that might arise since in the calculations of TFP growth I use values for the years in which the firm is in the "selected" sample, and thus I might observe firms at different point in the business cycle. Further details on this issue and on the construction of the TFP growth variables can be found in the Appendix D.

Finally, I try to control for factors, such as skill, technological opportunity, competitive pressure etc. that affect productivity growth in equation 5.10 and might also be correlated with innovation.[22] However, endogeneity might still be an issue in the model if unobservable factors (or factors unaccounted for in the analysis) that cause firms to grow more productive also cause innovations. I attempt to correct for this endogeneity using GMM techniques where I include in the matrix of instruments the inputs to the knowledge production function.

In all the productivity regressions, I include 4-digit industry dummies to capture differences in technological opportunity and 11 regional dummies to control for location specific effects. I also include the lagged level of TFP relative to the median firm in the 4-digit industry. This should capture the scope for learning, whereby plants further away from the frontier have more scope for learning and so catch-up and grow faster (see also (Griffith et al., 2004b)).

5.4.2 The Knowledge Production Function

As already described in the previous chapter, the knowledge production function (Griliches and Pakes, 1980) assumes that innovation output arises from innovation inputs. I consider the innovation production function

$$INNOV = f(IE_i, Z^{KNOW}) \tag{5.11}$$

[21] I also tried using lagged values of process and product innovation, from the three year period 1994 - 1996 derived from the CIS2 innovation survey. As described in section C.1.4, this information is only available for few firms.Indeed, this attempt was not very successful.

[22] For example, I control for changes in management practices, to proxy for changes in work organisation and I add competition variables, such as lagged firm market share.

where, IE_i is innovation expenditure (i.e. R&D investment, training costs etc.). Z^{KNOW} are other knowledge inputs into the ideas process (e.g. information from existing knowledge in the firm, or information from suppliers or customers) that the firm does not necessarily pay for.[23] An important feature of knowledge inputs Z^{KNOW} are that they are potentially transferable across organisations, given the public nature of knowledge. Thus I may write:

$$INNOV = f(IE_i, Z_i^{KNOW}, Z_{-i}^{KNOW}) \tag{5.12}$$

where I assume that innovations, either product or process, derive from the investment in innovation activities but also from the existing knowledge stock from other companies and institutions (suppliers, customers, or universities) and from the knowledge stock built up within the firms themselves. However, with the data at hand I cannot measure the existing 'knowledge stocks', thus I follow a different approach (as I did in chapter 3) and use a qualitative measure of the importance of information flows that a particular source has for a given firm.[24]

I therefore construct my measures of knowledge flows as follows. Firms are asked *"How important to your enterprise are the following as sources of information for new technological innovation projects or the completion of existing projects?"*. A number of information sources are provided (sources within enterprise, customers, suppliers and universities for example) and firms are asked to grade their importance on a 4-Likert scale ranging from 0 (not used at all) to 3 (very important), see also Cassiman and Veugelers 2002 for a similar argument. Although these questions do not capture the stock of ideas, they captures differences across firms in the flow of ideas from that stock. I briefly describe these knowledge flows (defined as Z_i^{KNOW} and Z_{-i}^{KNOW}) measures here, and refer for details to the appendix D. To measure Z_i^{KNOW} I use the reported importance of ideas from sources within the enterprise. To measure Z_{-i}^{KNOW}, I use the reported importance of ideas from various sources outside the enterprise. First, I consider the role of knowledge flows between the firm

[23]The data does not allow to know whether firms pay for the information they receive from the different sources.

[24]The rational is similar to that underlying the use of citation-weighted patents. However, the main limitation here is that we do not have a measure of 'knowledge stock'; while this might be less of a problem for knowledge stocks outside the firm, as explained below, the fact that we do not have a measure of knowledge stock at the firm level, might prevent us from capturing some relevant heterogeneity across firms.

and other enterprises within the enterprise group. Since there are other 18 external sources of information I group them together for convenience as follows. First, vertical sources information (from clients, customers or suppliers); second, market sources (from competitors). Third, commercial sources of information (from consultancy enterprises, research association or commercial R&D laboratories). Fourth, universities; fifth, free (from professional conferences, meetings, journals etc.); sixth, regulatory (from health and safety regulations; product standards; environmental regulations), and finally, government (from government institutes; training and enterprise councils).

Each source of ideas is graded from 0 to 3. When combining the idea sources together I used the maximum importance of any idea reported by the firm. Cassiman and Veugelers use the average importance reported but this would understate the importance of a certain source of information and overvalue others within a particular group, thus flattening the differences among information sources.[25] Caution must be taken in the interpretation of the variables Z_i^{KNOW} and Z_{-i}^{KNOW}, in order for these variables to really capture differences in knowledge flows I need to assume that there are no significance differences in the knowledge stocks built up at the firm level and external to the firm. This assumption is probably very restrictive: firms are likely to differ both in their internal knowledge stock and possibly also in the external knowledge they can access. Although my measure might partly capture this heterogeneity, a more conservative interpretation of the Z^{KNOW} variables is as a measure of the relative importance of different knowledge sources.[26] An additional concern arises because the Z^{KNOW} measures are based on self-reported ordinal information provided by the firm rather than on cardinal measures of importance of information flows. If firms anchor their scales at different levels this invalidates inter-firm comparisons.[27]

[25] I tested the robustness of my results to using both methods and actually they made little difference.

[26] Ideally I would have liked to construct a weighted measures of knowledge stocks, with the Z^{KNOW} variables as weights that capture the technological 'distance' between the firm and a particular source of information and knowledge stocks constructed at the level of each information source (e.g. universities, suppliers, trade fairs, etc.). Given the data at hand this has not been possible.

[27] If the metric used by firms is invariant over time then using fixed effects helps to ease the anchoring bias problem, because it uses intra-firm time variation rather than interfirm cross-sectional variation (see also Winkelmann and Winkelmann (1998)). I have tried this approach in the fixed effect logit equation reported in the previous chapter.

I also enter other variables that might indicate external knowledge flows: whether the firm is part of a group ($GROUP$), whether it has an international market or not ($EXPORTER$), is part of a British or foreign multinational enterprise ($UKMNE$ and $FOREIGN$ respectively) , whether it has cooperation agreement with other firms or institutions ($COOP$) and whether is part of a government programme on knowledge sharing ($PROGRAM$). Finally, to measure random factors such as luck, I add a random error term. I also add 4-digit industry dummies to proxy differing technological opportunities that might affect the flow of new ideas and regional dummies to proxy for geographical opportunities.

Thus the equation I estimate is:

$$\begin{aligned} INNOV_i &= \beta_1 \frac{IE_i}{P_iY_i} + \beta_2 Z_i^{KNOW} + \sum_j \beta_3 j Z_{-i,j}^{KNOW} + \beta_4 GROUP \qquad (5.13) \\ &+ \beta_5 EXPORTER + \beta_6 UKMNE + \beta_7 FOREIGN + \beta_8 COOP \\ &+ +\beta_9 PROGRAM + \beta_{10} ln(emp)_{1998} + \beta_{11} AGE \\ &+ +\beta_{12} StrucChange \\ &+ \lambda_I + \xi_R + u_i \end{aligned}$$

Differently from previous studies I estimate the knowledge production function for both product and process innovation. For process innovation, I have yes/no answers as to whether a process innovation had occurred. For product innovation, I have data on the fraction of sales accounted for by new and improved products. Since the questionnaire asks about the fraction of sales I used this as dependent variable. I use innovation expenditure normalised by sales, to measure intensity of innovation expenditure, as dependent variable. Innovation expenditure encompasses investment in R&D but also in training, acquisition of external knowledge etc. The normalisation aims at reducing measurement error issues, since if firms consistently misreport their turnover and expenditures (i.e some firms report in thousands and some in millions and they do this consistently) normalisation will help.[28] Thus if my dependent variable is process (product) innovation I use a probit (tobit) estimator.

[28]In the productivity growth equation I distinguish between radical and incremental product and process innovations. I will report the equations for novel product and process innovation as a robustness checks.

5.4.3 The innovation expenditure equation

The investment in innovation aims at increasing the quality of the firm's product and/or decreasing the marginal cost of production.

For a profit maximising firm that invests in innovation to increase its market share and/or improve its production efficiency the optimal level of innovation intensity, the ratio of innovation expenditure (IE) to sales (P_iY_i)[29]:

$$\frac{IE_i}{P_iY_i} = \frac{\frac{IE_i}{Y_i}\frac{\partial Y_i}{\partial IE_i}}{-\frac{P_i}{Y_i}\frac{\partial Y_i}{\partial P_i}\Xi_i} \tag{5.14}$$

Where Ξ represents the total marginal costs of innovation expenditure, which given the cost reducing role of innovation expenditure, will be less than the marginal cost of a unit of innovation expenditure by an amount which is proportional to the production cost reducing effect of this investment. $\frac{IE_i}{Y_i}\frac{\partial Y_i}{\partial IE_i}$ and $\frac{P_i}{Y_i}\frac{\partial Y_i}{\partial P_i}$ are the elasticities of output to innovation expenditure and prices, respectively. This stylised model can describe the heterogeneity in innovation investment decisions observed within and across industries, in that firms face different elasticities and different innovation total marginal costs.

Equation 5.14 says that IE_i depends negatively on costs, Ξ_i, (but positively on the cost reducing effects of innovation expenditure via the total marginal costs of IE): a firm where it is easier to implement process innovation, for example because of less organisational rigidities, will expect to get more marginal benefit from its innovation expenditure and hence spends more. According to this formula, innovation intensity is a decreasing function of the price elasticity of output and thus an increasing function of the degree of market power. Innovation expenditure increases with the elasticity of output with respect to innovation expenditure. This latter elasticity can be thought of as being composed of a demand related element, i.e. the elasticity of demand with respect to product quality and a "technological opportunity" element, the elasticity of product quality with respect to innovation expenditure. I try to capture both these effects in the empirical analysis.

Firms might decide not to invest if they face too low an elasticity of demand to product quality. this might be the case when the appropriability conditions in the industry are such that the competitors can quickly copy the new product introduced

[29]Equation 5.14 is a Dorfman-Steiner type first order condition, see also González et al. (2004)

by the firm. Similarly firms with poor technological opportunity, or high total costs of innovation (which encompasses cases of low cost reducing effect of innovation), that are too low too justify the innovation expenditure will optimally decide not to invest.[30]

Thus, in the econometric specification I take into account the fact that zero innovation intensity might be an optimal corner solution to the profit maximisation problem by specifying the innovation intensity equation as a Tobit (Wooldridge, 2002). The estimating equation 5.15 is a reduced form of the structural equation 5.14. The choice of the regressors, therefore, aims at expressing the endogenous and unobservable elasticities and costs in terms of observable and predetermined or exogenous factors that affect them.

$$(\frac{IE_i}{P_i Y_i})^* = \sum_j \alpha_{1j} X_{1j} + \sum_k \alpha_{2k} X_{2k} + \sum_h \alpha_{3h} X_{3h} + \lambda_I + u_i \qquad (5.15)$$

and we observe $\max\{0, (\frac{IE}{P_i Y_i})^*\}$

The variables that enter the vectors X_1, X_2 and X_3 are respectively:

X_1 : $SUBSIDY_i$, *%engineers and scientists*, *%other graduates*

X_2 : $MktSHARE_{1998}$, $EXPORT_{dummy}$, *Strategic protection*, *Formal protection*, *Info from* $Competitors_{4dig,9496}$,

X_3 : $GROUP$, $UKMNE$, $FOREIGN$, $ln(employ_{1998})$, $ln(age)$, Age_{dummy}, *Merger*, *Closure*, *Startup*

In X_1, I include factors that affect Ξ, the total marginal cost of innovation: whether the firm has received a subsidy (0/1 dummy), qualitative information on organisational rigidities, which I include as a 0/1 dummy. Finally I include the proportion of educated workers. This variable captures two opposite effects: on the one hand the marginal cost of an R&D employee is higher the higher his education level; this would impact positively on the marginal cost of an extra unit of innovation expenditure and thus decrease the optimal innovation expenditure; on the other, the presence of qualified personnel is likely to increase the ability to innovate and thus

[30]We exclude the possibility that firm might have negative innovation expenditure, i.e. the possibility that firm might 'disinvest' in innovation.

the cost reducing effect of innovation expenditure, thus increasing the optimal level of innovation intensity.

X_2 contains factors that proxy for the competitive pressure and appropriability conditions of the firm: thus I include the lagged (and thus assumed predetermined) market share of the firm and whether the firm is an exporter; the importance of formal (e.g. trademarks, patents and copyright) and strategic (e.g. secrecy, complexity of design) methods to protect innovation. $Info\ from\ Competitors_{4dig,9496}$ is an industry level measure of the importance of knowledge coming from competitors in the industry calculated from CIS2.

Finally, X_3 includes firm characteristics that proxy for unobservables that might affect innovation intensity. These include ownership structure, structural changes, size and age. I include industry dummies to account for technological opportunities and regional dummies to account for geographical opportunities.

5.4.4 Estimation procedure

I estimate two versions of the innovation part of the model, for product and process innovation. Both system are recursive and I estimate them using a two-step limited information maximum likelihood (LIML) approach (see Maddala (1983) and Amemiya (1983) and Murphy and Topel (1985) for a useful discussion on these class of models). Both contain the innovation intensity equation estimated using the approach suggested by Wooldridge (2002). In the first step I estimate a two-tiered model:

$$Pr(\frac{IE}{P_iY_i} = 0|X) = 1 - \Phi(X\gamma)$$

$$log(\frac{IE}{P_iY_i})|(X, \frac{IE}{P_iY_i} > 0) \sim Normal(X\beta, \sigma^2)$$

where in the first equation I model the probability that innovation intensity II is zero or positive, and in the second I assume that for positive values the conditional distribution of Innovation Expenditure on the regressors $X \equiv \{X_1, X_2, X_3\}$ is log-normal. From this first step I obtain

$$\frac{\widehat{IE}}{P_iY_i} = E(\frac{IE}{P_iY_i}|X) = \Phi(X\widehat{\gamma})exp(X\widehat{\beta}) + \frac{\widehat{\sigma^2}}{2})$$

In the second step I use $\widehat{\frac{IE}{P_iY_i}}$, the predicted innovation intensity from this first equation in the second maximum likelihood, and bootstrap the standard error to correct the asymptotic covariance matrix at this second step. The second step differ across the two versions of the model. In the specification for product innovation I include the predicted innovation expenditure in a tobit equation estimated as tobits. For process innovation the second step consists in estimating a probit for process innovation.

5.5 Results

5.5.1 Innovation and Productivity Growth

I start by looking at the effect of innovation output on productivity growth. The reason for doing so is that as noted by Griliches and Pakes (1980) and Crépon et al. (2000) what matters for productivity growth is the output of the innovation process rather than its inputs.

Column 1 of table 5.4 relates to the traditional R&D intensity approach in that it includes R&D intensity to productivity growth. The estimate of the returns on R&D in the productivity growth equation, where the dependent variable is the annualised TFP growth rate calculated over the period 1997-2001, as described in detail in Appendix D, is 0.6% but not statistically significant.[31]

A possible problem with column 1 is measurement error. The value of R&D reported in the CIS by firms that are part of a group might include R&D conducted at their site on behalf of other enterprises in the group or alternatively they might enjoy the benefits of R&D done in other enterprises in the group. Thus, in column 2 I report the results of restricting the sample to enterprises that are not part of a group. The coefficient increases to 69% but it is still not statistically significant.

In column 3 I use rather than a measure of innovation input a measure of inno-

[31]Schankermann (1981) discusses the problems related to double counting of R&D inputs in an extended production function frameworks. To be able to correct for double counting in the productivity growth equation I should also have longitudinal information on R&D personnel and possibly on capital stock used in R&D activities. However I do not have this information. Thus, I assume that R&D personnel does not grow in the period considered 1997-2001. Although this seems a strong assumption. The longitudinal evidence available from comparing CIS2 with CIS3 shows that the number of scientists and of R&D personnel remains stable over time.

Table 5.4: Estimates of productivity growth equation

	(1) R&D	(2) single	(3) patent	(4) innov	(5) GMM
$\frac{R\&D}{Sales}$	0.0062	0.6947			
	(0.1154)	(0.4305)			
$ln(Patent)$			0.0008		
			(0.0074)		
$Dummy_{patents}$			-0.0137		
			(0.0153)		
$Process_{innovation}$				0.0051	0.0016
				(0.0087)	(0.0139)
Novel Process				-0.0186	-0.0222
				(0.0128)	(0.0376)
% novel products				0.0827	0.0671
				(0.0463)*	(0.1394)
$\%new_{products}$				0.0157	0.0464
				(0.0160)	(0.0510)
Δc_i	-0.1076	-0.0809	-0.1113	-0.1061	-0.0716
	(0.0496)**	(0.0914)	(0.0479)**	(0.0479)**	(0.0396)*
$RelativeTFP_{i,t-1}$	-0.0478	-0.0578	-0.0507	-0.0514	-0.0569
	(0.0285)*	(0.0342)*	(0.0248)**	(0.0246)**	(0.0139)***
$MKTshare_{i,t-1}$	0.0305	-0.0074	0.0124	0.0564	0.0112
	(0.0819)	(0.0826)	(0.0735)	(0.0852)	(0.0280)
$ln(age)$	-0.0074	-0.0143	-0.0067	-0.0057	-0.0056
	(0.0051)	(0.0094)	(0.0048)	(0.0047)	(0.0041)
$Dummy_{age}$	0.0106	0.0101	0.0094	0.0102	0.0066
	(0.0076)	(0.0147)	(0.0073)	(0.0071)	(0.0056)
startup	0.0337	0.0102	0.0332	0.0290	0.0261
	(0.0243)	(0.0298)	(0.0242)	(0.0243)	(0.0211)
merger	0.0185	0.0459	0.0149	0.0149	0.0097
	(0.0107)*	(0.0259)*	(0.0105)	(0.0100)	(0.0079)
closure	-0.0179	-0.0432	-0.0188	-0.0202	-0.0129
	(0.0131)	(0.0296)	(0.0123)	(0.0123)	(0.0103)
Observations	643	281	678	678	674

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for plants in the same firm. In all columns the dependent variable is annualised TFP growth rate over the 1997-2001 period. Regressors included in all columns but not reported in the table are: 4-digit industry dummies, 10 regional dummies, year dummies for the years used in the calculation of TFP growth (see Appendix D) for details. In column 5, the value of the Sargan test of overidentifying restrictions 14.93 which under the null is distributed as Chi square with 13 degrees of freedom. The P-values is 0.31. Instruments used are information sources, financial and non financial support, technology push and demand pull dummies.

vation output, patents.[32] Again the estimated coefficient is positive but not statistically significant.[33]

Column 4 and 5 set out the results of estimating equation 5.10 and report the estimates of the coefficients of CIS type measures of innovation output on productivity growth: novel and new and improved product (measured as proportion of sales on total turnover) and novel and incremental process innovations (measured as 0/1 dummies). Column 4 reports the OLS estimates. The results show that the coefficient on incremental process innovation is positive but not significant, while the coefficient on novel process innovation is negative but also not statistically significant. The coefficients on product innovation variables are both positive, with the coefficient on the share of turnover due to new and improved products not significant, whereas the coefficient of novel product sales is a significant 0.08.

These results seem to suggest first that novel innovations plays a stronger role than incremental innovations and secondly that process innovation is not significantly correlated with TFP growth. The first result is in line with the work of Duguet (2004) who, using French data for the 1986-1990 period, shows that radical innovations are the only significant contributor to TFP growth.[34] The second result, although surprising at first, is also consistent with previous results using the CIS for the Netherlands by Klomp and van Leeuwen (2001) and for Sweden by Loof and Heshmati (2002). The negative coefficient on novel process innovation might suggest that this type of innovations take time to be implemented, leading to an initial fall in measured TFP growth.[35] We will investigate this issue further in table 5.5.

[32] I follow the traditional approach in the literature (Klette, 1996) and use the log of patents replace the log of zero patents with zero. We also include a dummy variables for observations with zero patents.

[33] I must note that the measurement of both the R&D and patents variable in the Community Innovation Survey is affected by several limitations. The R&D variable is recorded for the year 2000 and firms are asked only about R&D conducted in their 'reporting unit', rather than at the enterprise group level, thus the measure available might miss all R&D conducted in other locations of the same groups. The patent measure we use is the number of patents applied for during the 1998-2000 period. I do not know where the firm applied, i.e. European Patent Office or US Patent Office and I also do not know whether these patents were granted and how many citations they could receive. Thus, this measure of 'patents' is quite rough relative to the recent literature that use patents as a measure of output. The limitations of the two measure could partly explain the insignificance of the coefficients in the productivity growth regressions.

[34] Note, however, that the work of Duguet differs from this one in that Duguet does not distinguish between product and process innovation but rather he concentrates only on innovation 'height', i.e. incremental vs radical innovation.

[35] Such a preliminary dip is the basis of the macro work by Basu et al. (2003). Another possible explanation is that this negative correlation results from a timing issue: firms that undergo a

The OLS estimates might be inconsistent if the innovation output variables are endogenous. Thus, in column 6 we report the result of instrumental variable GMM estimation. As instruments for the innovation output measures we use the inputs to the knowledge production function.[36] The sign of the coefficients on the innovation variables remain unchanged after controlling for endogeneity of innovation output. In the notes to the table we also report the result of a Hansen test of overidentifying restrictions that cannot reject the validity of our instruments.

In all columns we control for initial productivity level of the firm relative to the median firm in the industry (at the 4-digit level), such a regressor is often used to proxy the scope for learning, i.e. plants further away from the frontier have more scope for learning and so catch-up faster (Griffith et al., 2004b). The coefficient is negative, thus suggesting that firms with a lower productivity will catch-up and grow faster. Additionally, we control for the age of the firm and for structural changes during the 1998-2000 period, as reported by the firm in the CIS survey. This should account for differences in learning opportunity and significant events that might both affect productivity growth and be correlated with innovation output. The estimated coefficients on age and on the structural change variables seem sensible: a non-linear negative effect of age and a negative coefficients on the self-reported variable for partial closure. Finally, we add controls for the competitive environment of the firm that might not be already captured by the industry dummies: the firm initial market share, this variable is never significant across all specifications.[37]

These results seem to be robust to the inclusion of other controls and other sensitivity analysis as shown in table 5.5.

The first column checks the robustness of the previous results to using different time periods to calculate the annualised growth rates. This implies also a change in the number of observations since the ARD is an unbalanced panel with gaps (for

crisis are more likely to introduce improvements in the production process, both technological and organisational (Nickell et al., 2001). Yet another explanation is offered by Klomp and van Leeuwen (2001). They suggest that the negative coefficient might reflect a positive long-run effect of process innovation on employment, achieved through increased competitiveness due to the higher efficiency. This is unlikely to be the case here since we do not really observe a long time series.

[36]The choice of which, follows from the discussion in chapter 4 and in the previous section.

[37]In unreported analysis we also checked the reobustness of our result to the inclusion of the firm's international profile, captured by the global engagement dummies exporter, UK MNE and foreign MNE. None of these effects are consistently significant across samples.

Table 5.5: Estimates of productivity growth equation. Robustness checks

	(1)	(2)	(3)	(4)	(5)
% novel products	0.1142	0.0680	0.0852	0.0718	0.0364
	(0.0849)	(0.0417)	(0.0471)*	(0.0452)	(0.0336)
$\%new_{products}$	0.0551	0.0251	0.0141	0.0134	0.0106
	(0.0407)	(0.0157)	(0.0160)	(0.0170)	(0.0160)
Novel Process	-0.0361	-0.0159	-0.0207		-0.0238
	(0.0337)	(0.0104)	(0.0131)		(0.0130)*
$Process_{innovation}$	-0.0025	0.0066	0.0059		0.0083
	(0.0188)	(0.0070)	(0.0086)		(0.0090)
Managerial change			0.0110		
			(0.0057)*		
$Process_{lowflexibility}$				-0.0067	
				(0.0102)	
$Process_{mediumflexibility}$				0.0041	
				(0.0079)	
$Process_{highflexibility}$				0.0135	
				(0.0182)	
Δc_i	-0.0827	-0.0993	-0.1244	-0.1158	-0.1222
	(0.0828)	(0.0493)**	(0.0472)***	(0.0486)***	(0.0516)**
$ln(age)$	-0.0068	-0.0084	-0.0043	-0.0056	-0.0047
	(0.0106)	(0.0044)*	(0.0048)	(0.0048)	(0.0054)
$Dummy_{age}$	0.0162	0.0103	0.0083	0.0102	0.0083
	(0.0149)	(0.0062)*	(0.0072)	(0.0073)	(0.0077)
$RelativeTFP_{i,t-1}$	-0.0078	-0.0446	-0.0467	-0.0505	-0.0419
	(0.0605)	(0.0222)**	(0.0254)*	(0.0245)**	(0.0309)
$MKTshare_{i,t-1}$	0.0549	0.0379	0.0583		0.0787
	(0.1483)	(0.0313)	(0.0851)		(0.1213)
%scientists & engineers					-0.0134
					(0.0277)
% other graduates					0.0678
					(0.0377)*
Observations	435	648	660	617	592

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for plants in the same firm. In column 1 the dependent variable is annualised TFP growth rate over the 1998-2000 period. In columns 2 to 5 the dependent variable is annualised TFP growth rate over the 1997-2001 period. Regressors included in all columns but not reported in the table are: 4-digit industry dummies, 10 regional dummies, year dummies for the years used in the calculation of TFP growth (see Appendix D) for details).

smaller firms).[38] Now, the sign of both incremental and novel process innovation is negative and the point estimate of the novel process coefficient is larger in absolute terms. This might suggest the presence of adjustment costs and a trial and error phase after the introduction of novel production processes. The significance of the coefficient of novel products has now dropped to 17%, but the point estimate is not significantly different from the one in column 4 of table 5.4.

In column 2 we use as dependent variable the annualised growth rate over the period 1997-2001 as we did in table 5.4, but we try to control for the possible measurement error introduced by matching reporting units that report at different level in CIS3 and in the ARD: we drop those reporting units that are multi-plant or part of a group and for which the ratio of employment in the ARD over that in CIS is above 1.5 and below 0.5.[39] The coefficients, although very marginally significant (e.g. the coefficient of novel product innovation is significant at the 10.3% level), have the same signs as in column 4 of table 5.4.

Column 3 aims at controlling for the effect of 'soft innovations' and at proxying for the unobservable quality of the firms' managers. To this aim, we include measure of organisational and managerial innovations. These changes are positively and significantly correlated with productivity growth and do not significantly affect the magnitude of the technological innovation outputs coefficients.[40]

In column 4 I investigate the insignificance of the process innovation coefficients. The data only provides a 0/1 measure of process innovation, either novel or incremental, but does not directly give a measure of the success of this process innovation as it does for product innovation, by providing a sales weighted measures of product innovation. Moreover the distinction of novel and non-novel innovation, although very relevant for product innovation, is possibly less useful in the context of process innovation. Thus, I try to construct a successful weighted measure of process

[38]In the table I only report the results from using only the 1998-2000 period. In unreported results I have experimented with other time periods, without obtaining very big different results from the ones reported in the tables.

[39]This entails dropping observations for 32 firms.

[40]An obvious extension would have been to study the effect of an interaction term between technological and managerial innovations. However, the number of observations for which there is a technological innovation but no organisational change is too small to allow separate identification of the interaction between technological and managerial innovations, since the correlation coefficients between the technological innovation measures and the interaction terms are always greater than 0.9.

innovation: using categorical information on "the impact that innovation activities have had on the enterprise" I construct a measure of process innovation that had a medium to high impact on improving production flexibility. The point estimates suggest that process innovations that are more successful in improving production flexibility are more positively correlated with productivity growth.

Column 5 investigates whether the inclusion of the education variable, which might capture unobserved quality of the firm's workforce, affect the estimated coefficients on innovation. The coefficient on the share of novel product innovation is still positive although smaller. Moreover, column 5 suggests that only the proportion of educated workers, with degrees in non scientific subjects, is correlated with productivity growth, over and above technological innovation, rather than scientists and engineers. These, on the other hand, as we will see in the next section are highly correlated with the innovation output of the firm.

5.5.2 The innovation expenditure equation

I now discuss the results of estimating the innovation expenditure, or innovation investment equation. As discussed above, I do have information on whether a firm has positive or zero expenditure, regardless of whether the firm has innovated or not. In this, the analysis differs from Crépon, Duguet and Mairesse who do not have information on innovation expenditure for non-innovators. Following Wooldridge (2002), I estimate a double-Hurdle model that accounts for the fact that zero innovation expenditures are a corner solution to the optimisation problem of the firm. The innovation output depend on the innovation intensity, and are modelled in a second equation, whose estimation I discuss in the next section.

In table 5.6 I present the estimation results of two specifications of equation 5.15. In the first two columns I report the results when including 4 digit industry dummies. In columns 3 and 4 I report the results of including three digit industry dummies but including measures of competition, sectoral growth and information from competitors at the 4 digit industry level. In columns 5 and 6 I also include measures of information flows from outside the firm and measures of the importance of knowledge capital stock within the firm and within the group, to proxy for the absorptive capacity of the firm (Cohen and Levinthal, 1989).

Table 5.6: Estimates of the innovation investment equation

	(1) level	(2) propensity	(3) level	(4) propensity	(5) level	(6) propensity
$ln(employment)$	0.2005	0.3953	0.1315	0.3666	0.1080	0.2835
	(0.0967)**	(0.0750)***	(0.0977)	(0.0682)***	(0.1010)	(0.0783)***
$ln(age)$	-0.0429	0.0907	-0.0428	0.0838	-0.0483	0.0455
	(0.0706)	(0.0714)	(0.0697)	(0.0680)	(0.0694)	(0.0774)
Age_{dummy}	0.0457	-0.2172	0.0128	-0.2388	0.0466	-0.1358
	(0.1286)	(0.1193)*	(0.1250)	(0.1160)**	(0.1225)	(0.1338)
$ln(MKT_{share_{i,t-1}})$	-0.3790	-0.2446	-0.3033	-0.1977	-0.3151	-0.2011
	(0.0825)***	(0.0659)***	(0.0852)***	(0.0592)***	(0.0895)***	(0.0705)***
$Export_{dummy}$	-0.0136	0.2985	0.0336	0.2177	0.0083	0.0884
	(0.1086)	(0.0951)***	(0.1111)	(0.0894)**	(0.1102)	(0.1011)
$Herfindahl_{4dig,t-1}$			42.3166	-13.7962	46.3305	-0.1421
			(20.1669)**	(11.4871)	(18.8133)**	(10.6848)
$\Delta grossoutput_{4dig,98-00}$			-0.2197	-0.1752	-0.2095	-0.0755
			(0.1254)*	(0.0902)*	(0.1301)	(0.1142)
group	-0.0743	0.0472	-0.1330	0.0629	-0.1496	-0.0348
	(0.0981)	(0.0973)	(0.0989)	(0.0943)	(0.0968)	(0.1092)
mneUK	0.1180	-0.1415	0.0393	-0.1026	0.0483	-0.1678
	(0.1457)	(0.1645)	(0.1450)	(0.1516)	(0.1397)	(0.1769)
foreign	0.0127	-0.1040	-0.0154	-0.0733	-0.0329	-0.0619
	(0.1417)	(0.1486)	(0.1388)	(0.1455)	(0.1384)	(0.1753)
financial support	0.7435		0.6638		0.6639	
	(0.1245)***		(0.1261)***		(0.1260)***	
$InfofromCompetitors_{4dig,9496}$			0.3198	0.4634	0.2254	0.1188
			(0.3262)	(0.2790)*	(0.3179)	(0.3373)
formal protection	0.1847	0.4595	0.1675	0.4106	0.0892	0.0840
	(0.1366)	(0.1362)***	(0.1356)	(0.1304)***	(0.1368)	(0.1440)
strategic protection	0.6019	1.4912	0.7090	1.4832	0.4161	0.6313
	(0.1586)***	(0.1404)***	(0.1531)***	(0.1337)***	(0.1463)***	(0.1553)***
$\%scientists\&engineers$	1.0667	1.5121	0.9511	1.3343	0.7758	0.7522
	(0.3546)***	(0.6823)**	(0.3690)***	(0.6285)**	(0.3616)**	(0.6277)
$\%othergraduates$	-0.2497	0.0897	-0.1664	0.1780	-0.3183	0.2292
	(0.4234)	(0.3324)	(0.3960)	(0.3201)	(0.3809)	(0.2822)
Internal Info					0.2511	1.3725
					(0.1609)	(0.1631)***
Info from group					0.3015	0.1865
					(0.1315)**	(0.1891)
vertical info					0.5950	1.0637
					(0.1823)***	(0.1738)***
Info from competitors					0.0862	-0.5624
					(0.1469)	(0.1996)***
Commercial Info					0.1926	1.0769
					(0.1654)	(0.2391)***
Free Info					0.1626	0.5563
					(0.1633)	(0.1895)***
Info from regulation					0.0805	-0.0360
					(0.1437)	(0.1719)
Info from universities					-0.3010	0.0510
					(0.1985)	(0.2784)
Info from government					-0.0425	-0.0109
					(0.1918)	(0.2846)
Observations	1879	1879	1849	1849	1849	1849

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for plants in the same firm. In columns 2, 4 and 6 I report the estimates of the first part of the hurdle model, i.e. estimates of the propensity to innovate equation. In columns 1, 3 and 5 I report the estimates of the level of investment, conditional on having invested. Regressors included in all columns but not reported in the table are: 3 indicators for structural change (startup, merger and closure) and 10 regional dummies. In columns 1 and 2 I also include 4-digit industry dummies, while in columns 3 to 6 I include 3-digit industry dummies.

The results in columns 1 and 2 suggest that larger firms are more likely to invest in innovation, and conditional on a positive investment decision they invest more. This result seem to contradict stylised fact three of Cohen and Klepper (1996), which states that for firms engaged in R&D there is no systematic relationship between the level of R&D and size. However, looking at columns 3 and 4, when I explicitly include controls for the competitive environment of the industry, I find that the effect of size on the amount of innovation investment (column 3) is not significant, in line with stylised fact three of Cohen and Klepper. This result remains unchanged when I control for absorptive capacity and external knowledge flows in column 5 and 6.[41]

The coefficients on the variables that control for the role of market power of the firm, show that the firms with high market share (at the beginning of the period) are less likely to invest, and if they invest they invest less. This result is robust across all three specifications.[42] The second competition measure used, export dummy,[43] seems also to suggest a positive correlation between innovation investment and competition. The third measure, the Herfindahl index of concentration, again, although less strongly suggest that firms in concentrated industries are less likely to invest but conditional on investment they invest more in innovation.

In columns 3 and 4 I find that both the probability of investment and the amount invested are negatively correlated (and significantly so at the 10% level) with the 4 digit industry specific growth patterns ($\Delta go_{4dig,98-00}$). However, this result is not robust to the inclusion of the internal and external knowledge flows measures as shown in columns 5 and 6.

I next report the effect of financial support, this variable is only included in the equation describing the 'second hurdle', i.e. only for the investors, since it is always

[41]In table D.2 I report estimates based on the same specification as columns 3 and 4 and columns 5 and 6, but where the dependent variable is R&D intensity rather than all innovation expenditure. The table shows that in the case of R&D the probability of investing is not correlated with size and the amount spent is correlated with size at the 10% level when I do not control for measures of absorptive capacitiy and knowledge flows but when I do (column 3 and 4 of table D.2) the variable size is not significant in either column.

[42]in the R&D investment equation, as reported in table D.2, the effect on the propensity to invest is not significantly different from zero.

[43]Note that the export dummy here is defined differently from the dummy variable "exporter" used in the previous chapter. This latter dummy was equal to one if the firm was a domestic non MNE that had positive exports. In this chapter the variable 'export dummy' takes value one in any firm, independently of its multinationality status, has positive exports.

zero for firms that did not invest. In all specifications (columns 1, 3 and 5) I find that financial support is correlated with higher level of investment.

What are the results concerning the effective appropriability conditions of innovation activities? I try to analyse this using two type of measures. The first uses 4 digit industry level information from CIS2 to calculate how important is competitive is the industry in producing innovation using information existing in the industry ($InfofromCompetitors_{4dig,9496}$), this variable also proxies for technological opportunities in the industry, and indeed the coefficient is positive in columns 1 to 4. The second uses information on the importance of methods of protections of innovations over the 1998-2000 period. I group these protection measures as formal, or legal, (patents, trademarks, copyrights, confidentiality agreements and registration of design) and as strategic (secrecy, complexity of design and lead time advantage on competitors).[44] The results show that the only measure of appropriability that is strongly positive and robust across specification is strategic protection. Moreover the negative coefficient on the importance of information from competitors in columns 5 and 6 seem to suggest that firms that can easily use information from competitors in the industry are less likely to invest in innovation. This result might be given two intuitive explanations: the first is that if firms can successfully copy from their competitors they need to invest less in innovation, the second is that if firms know that it is easy to copy from competitors in their industry they are less likely to invest because they are worried about competitors ripping off the benefits of their investment.[45]

The coefficients on the workforce skill structure suggest that a high presence of scientists and engineers is highly and positively correlated with both parts of the innovation investment equation, while conditional on the presence of scientists and engineers, the proportion of other graduates does not have any significance correlation with either the propensity to invest and the amount invested. This result

[44]The measures are constructed using the same method used to construct the information variables: I take the maximum score of the information on the importance of each protection method, graded from 0 (not used) to 3 (high importance), normalised to vary between 0 and 1.

[45]A third explanation, it might be that firms that rely on knowledge from competitors are actually the worst firm that would have invested little anyway. This latter explanation would suggest that the result is driven by unobserved heterogeneity among firms. If we had a larger panel I could try to investigate this latter issue in more detail, but the panel has a very limited number of observations and only two time periods.

suggest that innovation investment decisions are highly correlated with the knowledge capital already built up in the firm, which is partly embodied in its workforce. This result is confirmed by the positive coefficient on the relevance of information coming from within firm in column 6. The coefficients on the other sources of information seem to confirm the findings of the previous chapter, which highlighted the importance of vertical source of information and information from within the group. This latter variable is positively correlated with the level of investment but not with the probability of investment. Other information sources, 'free' (professional conferences, trade associations and fairs) and 'commercial' sources (consultants, private R&D labs), on the other hand, are positively correlated with the probability of investing but not with the amount invested.

In table D.2 in Appendix D.4 I report the results of estimating equation using as dependent variable R&D intensity rather than total innovation expenditure. I have already outlined differences concerning the role of size and market share. A third difference to note is that in this equation, conditional on size and industry effects, being a MNE, headquarter or affiliates, entails being much more likely to engage in Research and Development. This result confirms evidence that MNEs are more likely to have R&D laboratories and highlight once more that the measure of innovation expenditure used is much broader than R&D.

5.5.3 The knowledge production function

Column 1 of Table 5.7 reports estimates of a two-limits tobit model of the knowledge production function, where the dependent variable is the proportion of sales accounted for by new and improved products. The figures reported are marginal effects, conditional on positive innovation outcomes. The estimates show that the estimated returns to innovation expenditure is a reasonable and significant 18%. We also find that conditional on the innovation investment size and age of the firm are not significant, although the correlation between age and the proportion of new and improved products in total sales is negative. The estimates also confirm that globally engaged[46] firms are more innovative, although the coefficient on foreign affiliates is only borderline significant. I find that non-financial support by government is not

[46]Note that in this specification I define the variables exporter, UK MNE and foreign affiliates as in chapter 4 to make the results more comparable.

Table 5.7: Estimates of the knowledge production

dep. var	(1) new and improved products	(2)	(3) process innovation	(4)
$ln(employment)$	0.0042	0.0048	0.0331	0.0423
	(0.0023)*	(0.0024)**	(0.0078)***	(0.0107)***
$ln(age)$	-0.0045	-0.0034	0.0135	0.0204
	(0.0043)	(0.0043)	(0.0139)	(0.0190)
Age_{dummy}	-0.0004	-0.0020	-0.0366	-0.0226
	(0.0074)	(0.0073)	(0.0219)*	(0.0301)
Exporter	0.0128	0.0114	-0.0100	-0.0141
	(0.0068)*	(0.0067)*	(0.0201)	(0.0275)
group	-0.0097	-0.0096	-0.0455	-0.0554
	(0.0059)*	(0.0059)	(0.0182)**	(0.0239)**
mneUK	0.0062	0.0049	0.0121	-0.0254
	(0.0101)	(0.0100)	(0.0340)	(0.0385)
foreign	0.0091	0.0078	-0.0259	-0.0392
	(0.0097)	(0.0096)	(0.0285)	(0.0360)
non financial support	-0.0113	-0.0103	0.0241	0.0277
	(0.0101)	(0.0102)	(0.0353)	(0.0436)
cooperation	0.0352	0.0358	0.1078	0.1125
	(0.0061)***	(0.0061)***	(0.0290)***	(0.0344)***
Info from plant	0.0877	0.0818	0.2747	0.3088
	(0.0090)***	(0.0091)***	(0.0288)***	(0.0385)***
Info from group	0.0133	0.0158	0.0698	0.1026
	(0.0080)*	(0.0080)**	(0.0278)**	(0.0358)***
vertical Info	0.0418	0.0440	0.2508	0.2919
	(0.0104)***	(0.0104)***	(0.0342)***	(0.0437)***
Info from competitors	-0.0091	-0.0138	-0.1188	-0.1949
	(0.0097)	(0.0096)	(0.0327)***	(0.0419)***
Commercial Info	0.0149	0.0129	-0.0200	-0.0060
	(0.0096)	(0.0096)	(0.0341)	(0.0423)
Free Info	0.0337	0.0319	0.1021	0.1603
	(0.0101)***	(0.0100)***	(0.0329)***	(0.0430)***
Info from regulation	-0.0196	-0.0183	-0.0256	-0.0292
	(0.0090)**	(0.0089)**	(0.0296)	(0.0382)
Info from universities	-0.0007	-0.0004	-0.0316	-0.0352
	(0.0113)	(0.0112)	(0.0386)	(0.0498)
Info from government	-0.0194	-0.0214	0.0128	0.0011
	(0.0118)	(0.0118)*	(0.0399)	(0.0515)
Innovation expenditure/total sales	0.1823	0.1653	0.5370	0.2260
	(0.0322)***	(0.0613)***	(0.1115)***	(0.2828)
Observations	1836	1905	2513	1829

Notes: In columns 1 and 2 I report the conditional marginal effects of a tobit equation, with as dependent variable the proportion of sales accounted for by new and improved products. In column 3 and 4 I report the marginal effects of a probit equation with dependent variable a binary variable that is one if the firm has process innovated. IN column 1 and 3 I use the innovation expenditure variable as reported in the survey, in column 2 and 4 I use innovation expenditure calculated from the estimates of equation 5.15. Regressors included in all columns but not reported in the table are: 3 indicators for structural change (startup, merger and closure), 10 regional dummies and 3-digit industry dummies.

correlated with level of innovation outcome (and the unreported effect on the probability of being uncensored confirm this result). On the sources of information: I find that firms who cooperate have on average 3% more sales due to new and improved products. The coefficient on other information sources are in line with results from the previous chapter: internal information is strongly positive and significant, information from the group is positive although not strongly significant. Information from commercial and free, or institutional, sources are positively correlated with sales of new and improved sales. The effect of universities as information sources is positive and insignificant,while information from competitors is negative but again insignificant.

A possible issue with these results is one of endogeneity of the innovation inputs in this knowledge production function, that arise if unobservables or omitted variables that affect the innovation investment equation also affect the innovation outcome. I try to correct this endogeneity problem sing a two step approach, as described in the previous section, where my exclusion restrictions rely on the assumption that, conditional on innovation expenditure, financial support, market share, the Herfindahl index of concentration, the output growth potential of the firm, and measure of appropriability do not affect innovation output.

In column 2 of table 5.7 I report the results of the two-step estimation.[47] In column 2 I use the predicted innovation expenditure from column 5 of table 5.6, which is my favourite specification. As expected the point estimate decreases. Although the standard errors are not corrected, this result seems to suggest that the source of endogeneity might indeed be factors, such as unobserved firm fixed effects, e.g. managerial quality, that are correlated with both innovation investment and innovation outcome.

Columns 3 and 4 use as dependent variable process innovation. The first difference relative to the estimates using as dependent variable product innovation, is that now size is significantly correlated with process innovation. Secondly, while the global engagement dummies are not significant, the information coming from other firms in the group is strongly correlated with process innovation. As for product in-

[47]Note however, that correct inference from these results is not possible. I tried to correct the standard errors for the fact that I am using an estimated variable with bootstrapping. However, for problems of convergence of the likelihood function this has not been possible.

novation information from suppliers and customers and 'free' information from fairs and trade associations are positive and significant and information from competitors s negatively correlated with a positive process innovation.

Regarding the endogeneity issue, the pattern is similar to the one observed in columns 1 and 2; correcting for endogeneity of the innovation input lead to a decrease in the point estimates on the coefficient of innovation input, in line with the presence of unobserved firm fixed effects, however the marginal effect of innovation expenditure is now very imprecisely estimated. These results are at odds with other work where controlling for endogeneity leads to an increase of the innovation input coefficient (e.g. Loof and Heshmati, 2002, and Klomp and van Leeuwen, 2001).

In table D.1 in Appendix D.4 I report estimates of equation 5.14 when the dependent variable are measures of novel product and process innovations.

The estimates suggest that novel innovations, both product (measured as proportion of sales accounted for by products new to the market) and process, rely, relative to non-novel innovations, much more on sources of information internal to the plant, or from suppliers and customers, rather than from external sources of information, either commercial or institutional. Furthermore, I do not find that large plants have more novel process innovation than smaller plants.

5.6 Conclusions

This chapter has used matched data from the Community Innovation survey (CIS) and from the ARD to estimate the link between innovation and productivity growth, and two equations describing the innovation activity of firms: an innovation investment equation and a knowledge production function equation.

Firstly, one of the aims of this chapter was to show that the use of survey data still gives sensible and interesting results, especially when matched to quantitative performance data. Secondly, relative to previous research that used similar type of data for other countries, I used a specification of the production function (Klette, 1996) that rationalises different effects for product and process innovation and allows for the presence of non constant returns to scale and imperfect competition.

The results confirm that it is innovation output and not innovation input that affect productivity growth:novel product innovations are correlated with a higher productivity growth, controlling for the initial TFP level of the firm. I find that process innovations are negatively correlated with productivity growth. A further investigation of this result show that process innovations that the firm report as having increased the flexibility of production are actually positively correlated with TFP growth, thus suggesting the presence of adjustment costs. Finally, an interesting result is that conditional technological process and product innovation, managerial and organisational change is positively correlated with TFP growth.

On the result of innovation process, I find that competition, strategic protection methods, financial support and a high level of knowledge capital within the firm, measured by the workforce qualification and by the self-reported importance of internal information, are important determinants of the innovation investment decision. Also, the presence of suppliers and customers as source of relevant information are also correlated with a higher investment level.

The estimated returns to this investment seem rather plausible with an estimated return of 18% when I considered as measure of innovation the proportion of sales accounted for by new and improved products. An attempt to account for endogeneity of the innovation input suggests the presence of an upward bias in the tobit equation.

Beside investment and high absorptive capacity, as proxied by internal information, the main correlates with innovation output are, for both product and process innovations, cooperation and information from suppliers and customers.

Chapter 6

Employer Size Wage differentials

6.1 Introduction

The strong positive relationship between employer size and wages is an empirical regularity which seems to be as stable as the positive relationship between wages and education. This relationship has been established not only for the US (e.g. Brown and Medoff, 1989 and more recently Troske, 1999 and Oi and Idson, 1999 for a recent review of the literature) but also for other industrialized countries (see, for instance, work by Morrisette, 1993 for Canada, Main and Reilly, 1993, for Great Britain, Rebick, 1993, for Japan, Albaek et al., 1998 for the Scandinavian countries, and Schmidt and Zimmermann, 1991, for Germany). However, there is no clear explanation for the existence of the firm size wage differential. In a systematic investigation on this issue, Brown and Medoff note that *the size wage differential is one of the key differentials observed in labour markets. It is particularly interesting because, unlike the union wage differential, it exists in the absence of an obvious agent, one of whose goals is its existence.*

The variable 'employer size' combines a multitude of different determinants, and various plausible explanations for firm size differentials have been brought forward.

The rationale behind these explanations is that the size-wage effect is due either to differences in measured and unmeasured dimensions of labour quality, to compensating differentials caused by different job characteristics, or to differences in compensating policies among different sized employers.

One popular explanation for size wage differentials is that larger firms employ workers of higher quality. There are various explanations for why this may be the case: capital-skills complementarities (Hamermesh, 1980), higher innovation rates (Oi, 1991); skill complementarity between workers (Kremer, 1993) and matching between high ability entrepreneurs with high quality workers (Lucas, 1978 and Oi, 1983). These explanations predict that high ability workers will sort into large firms. Alternative models for which differences in wages between small and large firms are due to differences in screening costs (Garen, 1985) suggest that larger plants are likely to emphasise formal qualifications and credentials more than smaller firms because of higher costs of acquiring detailed information about workers' quality and, conditional on formal qualifications, they might employ workers of less unmeasurable ability than smaller firms.

Explanations based on efficiency wages theories (see Bulow and Summers, 1986), on rent-sharing hypotheses (Akerlof and Yellen, 1990 and Weiss, 1966) and explanations that refer to the type of jobs and tasks in differently sized firms (Masters, 1969) suggest that firms size differentials exist also for workers of same ability. Dynamic monopsony models reach similar conclusions (Burdett and Mortensen, 1998) and (Manning, 2003).

On the level of empirical implementation, hypotheses that size wage differentials are due to larger firms employing higher quality workers imply that, conditional on workers' unobserved ability, the wage differential should vanish. However, longitudinal studies that control for unobserved ability using first differences or fixed effects methods, have confirmed that unobserved heterogeneity leads to upward biased estimates in OLS level regressions, but does not account entirely for firm size wage differentials.

A limitation of these empirical tests is that they need to assume that unobserved ability (as well as observable measures of ability, e.g. education) is equally valued in small and large firms so that unobserved fixed effects can be differenced out in first difference or fixed effects regressions. However, this might not be the case. Gibbons et al. (2002), in a study of occupational and interindustry wage differentials show that when unobserved ability is valued differently in different firms, first differencing does not provide consistent estimates of the parameter of interest.

This chapter deviates from the assumption that the productivity differential between a high ability worker and a low ability worker is equally valued in firms of different size, on the lines of Gibbons et al.. The underlying model is a one factor model, in the sense that a high ability worker is more productive in any firm; however workers' ability is differently valued in different firms. As a consequence, if higher ability workers are better matched with larger firms, then firm size effects occur even conditional on fixed effects (see also Gibbons and Katz, 1992 and Gibbons et al., 2002). The analysis also encompasses an additional dimension explaining the productivity of a given worker in a given firm. Workers do not know their optimal match, and search. Search induces mobility, which is not assumed exogenous (differently from, for instance, Abowd et al., 1999).

I conduct the empirical analysis using a unique administrative data set, the *Institut für Arbeitsmarkt und Berufsforschung* (IAB) employment sample, which covers 1% of the German labour force over the period from 1975 to 1995. From this data source, I construct a data set of complete work histories of about 34000 young male workers, from entry to the labour market onwards. The wage information is very precise, and refers to average daily wages over employment spells, so that I can construct exact wage history variables on work experience and firm tenure. In addition to characteristics of the individual, such as age, education, and marital status, I observe a number of characteristics of the establishment in which the worker is employed. I observe industry and location at a very detailed level. Most importantly, I observe the exact number of employees in any year, and in any establishment in which any worker in the sample has been employed. This information is available for the period between 1980 and 1995. This continuous variable on employer size avoids measurement error problems, that are instead present with categorical firm size data (see Albaek et al., 1998 for a discussion), and it allows longitudinal analysis within the plant.

Furthermore, some of the previous empirical analysis based on worker level data has been limited by the unavailability of various aspects of firm quality. The IAB data allows me to investigate a number of issues which could not be addressed with previous data sets, since I have some unique information about firm characteristics, sometimes cited for contributing to firm size differentials. For instance, the data provides information on the skill mix within the firm at the time of the worker's employment, thus I can investigate the existence of possible complementarities between workers' quality in larger firms. Additionally, from the establishment size variable, I am able to construct a variable on the firm's age, the firm's closure, and the past growth of the firm. The firm closure information allows me to identify displaced workers, or "exogenous movers", which is important for the identification strategy, as explained below.

This chapter does not intend to provide a conclusive explanation for why firm size differentials exists; rather it intends to provide estimates of the firm size effects which are not contaminated by differences in the ability mix, and the presence of workers unobserved ability valued differently in differently sized firms. Furthermore, it tries to eliminate the bias which results from endogenous mobility even in difference equations.

The chapter is structured as follows: in the next section I briefly review previous hypotheses on size wage differentials, in section 6.3 I describe the model and some empirical predictions, in section 6.4 I describe the dataset and the sample used. I also present descriptive evidence on differences in wages, workers' characteristics and mobility across firms of different sizes which support both the existence of a comparative advantage and a 'true' employer size effect. In section 6.6 I present the empirical results and section 6.7 concludes.

6.2 A quick review of the literature

While there are well-established empirical results pointing to the existence of a wage premium, at a theoretical level there is still much investigation to be done to establish such a phenomenon. The analysis of the link between earnings and firm size seems to suffer from the fact that the variable "employer size" is incompatible with a stringent causal concept. It combines a multitude of different determinants. This is a disadvantage since several theoretical interpretations can be adduced to explain the confirmed link between firm size and earnings.

The explanations for explaining size wage differentials can be divided in two broad categories. First, the size wage differential is due to a higher productivity of workers in larger firms, so that workers with high measured and unmeasured ability would sort themselves in larger firms. Second, there is a wage premium paid to the worker which is not related to his productivity, but which is the result of a positive relationship between firm size and the costs of either information acquisition, or screening and monitoring. In this latter group of models high ability workers are not necessarily matched with larger firms.

There are various explanations for why larger firms employ workers of higher quality. Hamermesh (1980) for instance suggests that capital and skills are complementary. Due to economies of scale and preferential access to credit in imperfect capital markets, larger firms are more capital intensive, and able to employ higher quality labour. Similarly in Oi (1991) large firms, being more innovative and more capital intensive, need more qualified and specialised workers and seek a lower rate of workforce turnover. Therefore firm specific human capital accumulation takes place primarily at large firms and plants.

Kremer (1993) suggests that tasks are more complex in large enterprises because they adopt more advanced technologies. This induces greater skill complementarity between workers (O-ring production function) and therefore higher returns to human capital in larger plants. Oi (1983) argues that large firms need better quality workers. In Oi's model (1983) the matching of high ability entrepreneurs with high quality workers generates the size wage differential. As in Lucas' (1978) model of the size distribution of firms, entrepreneurs have an endowment of time and they decide how to allocate it to management and supervision. More able entrepreneurs manage larger workforce but have a higher opportunity cost of monitoring. In equilibrium better entrepreneur hire more productive workers who are characterized by lower supervisory costs. One of the implications of the model is that returns to labour quality increase with firm size, i.e. that the wage structure is convex. Similarly, in the presence of incomplete information about the workers' ability, firms may differ in their wage structure according to differences in the cost of screening mechanisms. Garen (1985) for instance suggests that larger plants have higher costs of acquiring detailed information about workers' quality and as a consequence, find it optimal to choose a more favourable compensation scheme for workers' of a given observable quality. In fact, Garen's model predicts that there is a negative correlation between the returns to observable and unobservable measures of quality: conditional on measurable workers' quality, such as education, qualification and experience, larger firm will employ workers of less unmeasurable ability.

Hypotheses that allow for heterogeneity in wages, conditional on workers' ability are based on efficiency wages theories (Bulow and Summers, 1986), rent-sharing

(Akerlof and Yellen, 1990) and (Weiss, 1966) and union avoidance hypothesis. Efficiency wage models point to discrepancies in technology and/or product quality as a possible explanation of the differences in wages according to size. Monitoring is more difficult in larger firms than in smaller firms; the cost of turnovers is higher and shirking has great negative effects; and productivity is more sensitive to wages. Larger firms exceed the market wage rate to reduce fluctuations and to offer incentives for a steady and involved work effort. The leading argument for rent-sharing as an explanation for size wage differentials is that larger firms are more likely to have monopoly power and they may share some of the monopoly rents with their workers, it being reasonable that excess profits lead to wage premiums especially when the labour force is organised as it is in large firms. In fact, the assumption underlying the work of Weiss, 1966 is that large employers are more likely to be unionised, since the working conditions and the scale of activity in larger plants are more likely to make workers receptive to unionisation. This results in higher wages. A different analysis, using a closely related argument and yielding the same result, is that is that large employers face a great threat of unionisation and therefore tend to follow a strategy of positive labour relations. Large non-unionised employers may try to avoid unionisation by conducting a policy of positive industrial relations including higher wages, more benefits and better working conditions. As a result, union wage and benefit differentials should vary inversely with size. The conclusion to both the union avoidance hypothesis and the union demands hypothesis is that the oligopolistic structure allows workers to obtain higher wages.[1] The empirical findings of Arai (2003) do not seem to support the role of rent sharing as an explanation for the size wage premium, since this premium is still significant after controlling for profits.

Another strand of explanations refer to the type of jobs and tasks in differently sized firms. Masters (1969) suggests that working conditions in large firms are worse than in small firms, and that firms size differentials may be simply compensating differentials. For instance, there is increased work division, a more impersonal work atmosphere, greater reliance on rules, less freedom of action and scheduling, longer

[1] Note that, as reported by Schmidt and Zimmermann (1991), collective bargaining in Germany is mainly organised on an industry level and thus firm size can be expected to mirror industry characteristics. Therefore to test for these latter hypotheses (Union Avoidance and Union Demand) one can include explicitly sectoral dummies. Contrary to the case of the Unites States, including a variable for individual union status would not have a positive effect on wages in Germany since collective contracts also cover non-members.

commuting. Thus, larger employers have to compensate prospective workers of a given quality for the unattractive features of the job by paying a higher wage. However, empirical work, such as Troske (1999), has shown that controlling for working conditions does not explain size wage premiums.

Some authors have suggested that firm size effects are due to internal labour markets offered by larger firms (Doeringer and Piore, 1971). The literature on internal labour markets provides a possible explanation for the positive relationship between firm size and wages and between firm size and tenure: internal labour markets would represent a screening device and an incentive for human capital investments. Internal labour markets facilitate the evaluation of workers' performance, since it is easier to collect information on the employee and ensure a higher return of specific human capital investments. This is thanks to reduced employee initiated turnover and a reduction in any diffidence of older workers in imparting their knowledge to new employees. Small firms seem to have higher failure rates and higher employment variability Dunne et al. (1989). Larger firms may, therefore, find it profitable to exploit their inherent size advantage for promoting within-firm job mobility. They can develop long-term relationships with their employees, offer on-the-job training, career growth and alternative types of jobs within the organisation due to lower failure probability (Idson, 1989 and Idson, 1996 and Winter-Ebner, 1995).

More recently Burdett and Mortensen (1998), in a model of on-the-job search with labour market frictions and unemployment, present a theory consistent with larger firms having lower turnover rate. In their model, firms offer higher wages to reduce quits and at the same time attract workers from low wage firms [2] and a unique wage distribution exists for homogenous workers. In this distribution wages increase with firms' size, since firms are faced with an upward sloping labour supply.[3] Results that support this idea are provided in Green et al. (1996).[4]

[2]Employed workers have higher reservation wages than unemployed workers, since they always have the option to stay with their current employer

[3]In the literature this model has been defined as a dynamic monopsony model (Manning, 2003) because the job market frictions make it possible for the firm to lower its wages infinitesimally without loosing all of its workers or increasing them to keep a larger fraction of the workforce without attracting all of the workers in the market.

[4]However, they cannot exclude other the validity of other explanations.

6.3 The econometric Model

6.3.1 The intuition

I will sketch the assumptions of the model underlying the econometric specification. The model assumes that workers are differently productive in different firms and search for the location of their optimal match, and firms and workers learn about the match quality. This creates mobility which is not exogenous (different from, for instance, Abowd et al., 1999). The model is a one factor model, in the sense that a high ability worker is more productive in any firm; however, workers' ability is differently valued in different firms. In particular, larger firms may value a worker's ability more than small firms. As a consequence, if higher ability workers are better matched with larger firms than with smaller firms, then firm size effects occur even conditional on fixed effects (see also Gibbons and Katz, 1992).

The model contributes to the existing literature in many respects. I highlight the differences with previous models. As I described in the previous section, in the traditional approach, ability is correlated with firm size. This leads to the conclusion that OLS estimates of the size elasticity are biased and inconsistent. The solution to this problem has been to treat ability as an unobservable fixed worker effect and to obtain consistent estimates using first differences or fixed effects models (see figure E.1 in appendix E.2). The main limitations of these models is that ability is assumed to be equally valued in employers of different size and thus mobility is assumed exogenous. Gibbons and Katz (1992) and Gibbons et al. (2002) have developed an alternative approach based on a comparative advantage model. The Gibbons and Katz and Gibbons et al. models have not been explicitly adopted to study size-wage differentials, however, one can easily apply their idea to the analysis of size wage differentials. Gibbons and Katz assume that ability is differently valued in different firms. In their model learning about workers' ability generates mobility across sectors. One of the main implications of the model is that there are no "true" sector specific advantages. Thus, wages increase with ability, but they increase more in large firms relative to small firms, but the wage of low ability workers will be higher in smaller firms while the wage of high ability workers will be higher in larger firms (see figure E.2 in appendix E.2). The unobserved individual fixed effect is valued differently across different sectors, so that it cannot been differenced out using first difference or fixed effects estimations methods.

The approach here departs from Gibbons and Katz because it encompasses the presence of comparative advantage but also allows for the existence of true firm size effects (see figure E.3 in appendix E.2).

The mobility decision has been modelled in several ways. Farber 1999 presents a simple model of mobility. It assume that workers search on-the-job for a better match. In each period the worker receives a wage offer, drawn from a wage offer distribution. He will accept the offer if this exceeds his current wage.

Thus, in such model of job mobility, in every period t the worker draws from a truncated distribution of wage offers. However, if the worker loses his job for exogenous reasons, e.g. for firm closure, he will have to draw from the whole distribution.

6.3.2 The empirical specification

Consider a level wage equation (which could be derived from a simple human capital model):

$$\ln w_{it} = \alpha_0 + \delta_1\, x_{it} + \delta_2\, z_{j(i,t)t} + \gamma \ln S_{j(i,t)t} + \eta_i + \mu_{ij(i,t)} + \phi_j(i,t) + u_{it} + T_t\,, \quad (6.1)$$

where $\ln w_{it}$ are log wages of individual i employed with firm j in period t, x_{it} are individual specific characteristics (including education, tenure, and labour market experience). The size of establishment j employing individual i in period t is given by $S_{j(i,t)t}$, and $z_{j(i,t)t}$ are other establishment characteristics.[5]

The term η_i is an unobserved individual specific heterogeneity component, $\mu_{ij(i,t)}$ is a time invariant match-specific productivity component, $\phi_j(i,t)$ is an unobserved firm fixed effect and u_{it} is a transitory idiosyncratic shock to wages. Finally, T_t are aggregate wage shocks, which I will model with time dummies.

The parameter I am interested in is γ, the effect of establishment size on wages.

[5] x_{it} is a vector of individual characteristics: cubic polynomial in experience, cubic polynomial in tenure, occupation and educational qualification at labour market entry. $z_{j(i,t)}$ is a vector of time varying and time invariant firm characteristics: the educational composition of the plant, i.e. percentage of skilled workers and percentage of university/*Fachochschule* graduates, which is a time varying variable, and the time invariant plant specific characteristics industry and region.

Straightforward OLS estimation of equation (6.1) leads to unbiased estimates of γ only if

$$\mathrm{E}(\eta_i + \mu_{ij(i,t)} + \phi_j(i,t) + u_{it}|x_{it}, z_{j(i,t)t}, S_{j(i,t)t}, T_t) = 0 \tag{6.2}$$

This is unlikely to be the case for a number of reasons. First, unobserved ability η_i may be correlated with firm size: if for some reasons high ability workers sort into larger firms, then this leads to an upward biased coefficient of the firm size variable. Second, sorting may lead to a correlation between the match specific effect μ_{ij} and firm size. Again, if high ability workers are better matched with larger firms, then this leads to an upward biased estimate of γ. Third, good quality firms, with high ϕ, are likely to be large and offer higher wages.[6]

To eliminate the possible bias induced by individual specific heterogeneity, many papers have estimated fixed effects or difference equations:

$$\begin{aligned}\Delta \ln w_{it} &= \delta_1 \, \Delta x_{it} + \delta_2 \, (z_{j(i,t)t} - z_{j-1(i,t-1)t-1}) + \gamma(S_{j(i,t)t} - S_{j-1(i,t-1)t-1}) \\ &+(\mu_{i,j(i,t)} - \mu_{i,j-1(t-1)}) + (\phi_j(i,t) - \phi_{j-1(i,t-1)}) + (u_{it} - u_{i,t-1}) + \Delta T_t\end{aligned} \tag{6.3}$$

Where $j(i,t)$ might be equal or different from $j-1(i,t-1)$.

If unobserved ability is not equally valued in firms of different size, and workers search for firms which exploit and reward their full productivity potential, then mobility is endogenous, and the change in match quality is likely to be correlated with firm size across firms, leading to biased estimates also in a difference equation:

$$\begin{aligned}\mathrm{E}((\mu_{ij(i,t)} - \mu_{ij-1(t-1)}) + \phi_j(i,t) - \phi_{j-1(i,t-1)} + (u_{it} - u_{it-1})|\Delta x_{it},) \\ (z_{j(i,t)t} - z_{j-1(i,t-1)t-1}), (S_{j(i,t)t} - S_{j-1(i,t-1)t-1}), \Delta T_t) \neq 0\end{aligned} \tag{6.4}$$

Similar problems occur when considering wage growth across firms only, i.e. when $j(i,t) \neq j-1(i,t-1)$:

[6] An additional source of endogeneity might be caused by idiosyncratic shock u_{it} carrying over to both workers' wages and firm size. I will come back to this issue later.

$$\mathrm{E}((\mu_{ij(i,t)} - \mu_{ij-1(t-1)}) + \phi_j(i,t) - \phi_{j-1(i,t-1)}) + (u_{it} - u_{it-1})|\Delta x_{it}, \quad (6.5)$$
$$(z_{j(i,t)t} - z_{j-1(i,t-1)t-1}), (S_{j(i,t)t} - S_{j-1(i,t-1)t-1}), \Delta T_t, STAY = 0)$$

where I condition on the mobility decision in addition. There is bias due to sorting (better individuals sort into firms with better wage offers) and due to selection (only those individuals who obtain high outside offers change firms).

Now consider wage growth within firms only. In this case, I obtain

$$\Delta ln(w_{it}) = \delta_1 \, \Delta x_{it} + \delta_2 \, \Delta z_{j(i,t)t} + \gamma \Delta S_{j(i,t)t} + (u_{it} - u_{i,t-1}) + \Delta T_t \quad (6.6)$$

where:

$$E(u_{it} - u_{i,t-1}|\Delta x_{it}, \Delta z_{j(i,t)t}, \Delta S_{j(i,t)t}, \Delta T_t, STAY = 1) \quad (6.7)$$

The firm fixed effect and the worker firm match component, as long as they are assumed constant over time, drop out of this expression. However, I restrict the sample now to workers who do not change firms, introducing a selection bias - a positive transitory shock may induce the worker to stay with the firm.[7].

I implement the following estimation strategy. I base the estimation equation on (6.6). I estimate within firm wage growth equations, and control for possible selection due to positive wage shocks. To do that, I estimate in a first step a reduced form probability equation:

$$Prob(CH = 0) = f(x_{it}, z_{jt}, I, lnS_{ijt}, \Delta T_t) \quad (6.8)$$

where I are our instruments. To identify firm size effects in equation (6.6), I need variables which, conditional on Δx_{it} and $\Delta zj(i,t)t$, do not affect wage growth within firms, but which do affect the probability that the worker stays with the firm. I use two sets of instruments. Firstly, I assume that, conditional on experience

[7]An additional source of endogeneity bias arises because positive transitory shocks are likely to be correlated with change of firm size, inducing a correlation between $(u_{it} - u_{i,t-1})$ and $(S_{j(i,t)t} - S_{j(i,t)t-1})$

and education, age does not affect wages. Age does however affect mobility, with older workers being less mobile than younger workers. Job separations are likely to entail risks and costs that will vary across workers according, for instance, to his marital status and to whether he has children: workers who are married and have children will be less likely to take risks, and thus more likely to stay with the same employer. Thus, I include a dummy for marital status and for whether the worker has children in the mobility equation. Secondly, the model suggests that workers learn about the quality of the match while being in the labour market. They then change firms only if the new match is superior to the old match. Accordingly, they draw from a truncated match distribution, where the average truncation point depends on how long they have been around in the labour market. Now suppose the worker loses his job because of some exogenous event, like a firm closure.[8] Then after job loss, and if compensation is independent of his former match quality, he will be forced to draw from the average distribution of job matches and not from the truncated distribution. Accordingly, when comparing two identical workers who only differ in the fact that one worker has been exogenously displaced in the past, then the displaced worker is more likely to accept at any point in his employment history a wage offer. Following this line of argumentation, I use the number of past displacements as an instrument for our mobility equation.

Thus the instruments I use are age, marital status and number of displacements before the current jobs.[9]

[8]Many studies that estimate returns to tenure have used sample of displaced workers (e.g. Dustmann and Meghir (2004)) using the same dataset. Gibbons and Katz (1992) use displaced workers to estimate inter-industry wage differentials. I explain below why restricting the analysis to a sample of displaced workers would not help identification in this case

[9]Previous cross-sectional work that has tried to control for the endogenous mobility, or more precisely endogeneity of firm choice include the study of Idson and Feaster (1990) and Main and Reilly (1993). Idson and Feaster (1990) argue that employer size is a decision variable based on an interaction between employer demand and workers' labour supply decisions. They try to correct for non-random sorting of workers using an ordered probit to predict firm size attachment and then correct the wage regression for selectivity bias. Their findings suggest that there is a non-random sorting of better educated workers into big firms, whereas small firms attract those workers with a high individual drive and level of independence. Main and Reilly (1993) also use an ordered probit model to predict worker's attachment to a given plant size. For identification, they use a set of variables, number of dependent children and their age group, that describe family characteristics. The rationale behind their choice is that these factors affect the choice of employment stability. The finding are not supportive of a non-random selection process into differently sized employers.

6.4 The Data and the Sample

The empirical analysis uses a one percent random sample of all employees in Germany for the period 1975-1995, the *IAB Beschftigtenstichprobe*, from the German Social Security Record, known as the Historical File (HF) of the Federal Employment Office. The information included in this data set is gender, nationality, education, gross earnings, and reasons for the interruption of the spell. The basis for this data set is an integrated procedure for health-, retirement-, and unemployment insurance,[10] which requires establishments to report any beginning and termination of an employment relationship covered by social security. In addition, establishments have to provide information on ongoing employment relationships at the end of each calendar year. The information provided includes gross earnings, gender, nationality, education, job position, and occupation. For each of these employment spells, I observe the average daily wage. Due to the administrative nature of our data set, wages and employment spells are very accurate. Measurement error is thus negligible.

I construct from this data base a sample of male workers whom I observe from their entry in the labour market onwards.[11] I require all workers to be at most 15 in 1975 (which is the youngest age at which workers can join apprenticeship schemes). Workers with A-levels at labour market entry are included in the sample when they were 19 or younger in 1975. This is the minimum age students can graduate from high school. Workers with university degree were 23 or younger in 1975.[12]

From this sample I construct complete work histories for young workers from labour market entry onwards up to 21 years in the labour force.

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[10]The HF data is supplemented by an additional data source, the so-called *Leistungsempfngerdatei*, which contains spells for individuals who receive unemployment benefits from the Federal Employment Office.

[11]Note that I restrict my sample to West Germany.

[12]Workers without *Abitur* (secondary school qualification) to be between 15, since 15 is the earliest they can leave school and 19 at labour market entry (or at the start of the apprenticeship) to include all workers with ten years of general schooling plus two years of vocational schooling. Workers with *Abitur* are included in the sample when they were 19, age at which students graduate from high school or younger in 1975, but not older than 21 at labour market entry, to include all high school graduates who complete their compulsory military service (1 year and 3, or 6 months) before entry in the labour market. Workers with a university/polytechnic degree at labour market entry must be 24/23 or younger in 1975, since this is the minimum age at which German students can graduate and at most 29/27 at labour market entry, to allow for the completion of the compulsory military service and for the prolonged duration of tertiary degrees.

The data set covers only employees which pay social security contributions. This excludes civil servants, the self employed, and individuals in marginal jobs. Also excluded are employees whose earnings fall below the threshold that makes social security contributions obligatory; the data set is therefore left-truncated. However, this is a minor problem for the sample I are using, where I only include male workers who are in regular full-time employment. Moreover, as many administrative data sets, our data is right-censored at the highest level of earnings that are subject to social security contributions.[13] In our overall sample, top-coding is not a serious problem for apprenticeship skilled workers and unskilled workers; less than 0.5 % of all wage observations are top-coded. It is however a problem for university graduates: for them 11.74% of observations are top-coded. Thus, I decided to conduct the empirical analysis separately for workers from this group and to restrict it to their first 5 years in the labour market. During this period, top coding is again negligible (less than 10%).[14]

The dataset also contain a plant and a firm identifier. By aggregating up on the entire data base of 100% of the workforce, aggregate individual characteristics have been created at the establishment level, and matched to the data. The additional information I obtain from this include the within-firm educational structure (distinguishing between the percentages of low skilled, medium skilled, and high skilled workers), plant size and plant closure information, with the latter variable being available for the years between 1980 and 1995. This information is available for all firms over this period which ever employed any worker in the IAB sample.

The size of establishments is included as a continuous variable. This is a notable advantage. Often the precise number of employees is not available, so that many studies report estimated coefficients for various size classes. Moreover, being continuous, it does allow longitudinal analysis within the plant, which is not possible in studies of industry wage differential or in studies that only have categorical information on size, or a measure of size likely to be heavily affected by measurement error (e.g.: survey data).

A potential disadvantage of the dataset is that for multi-plant firms I only know the size of each single establishment and not of the entire firm, since in the data

[13]The threshold varies over the years

[14]See also table (E.1) in Appendix E.1

there are no identifiers that allow to aggregate the size of each establishment up to the firm level. Thus, I cannot investigate whether establishment size and firm size have separate independent relevance for wages.[15]

Appendix E.1 defines the variables I use in the empirical analysis.

6.5 Mobility, Establishment Size and Wages

The sample used for the descriptive and regression analysis includes 324,865 observations, from the year 1980 to the year 1995: 34,033 full time workers in 63,912 plants. Of these 34,033 full-time workers: 6,580 are unskilled, 23,648 have an apprenticeship and 4,648 hold a university or polytechnic degree.

Table 6.1 displays plants' and workers' characteristics in the sample, according to firm size. I categorise firm size into four classes: small firms with less than 20 workers, medium sized firms with less than 100, large, 100 to 999, and very large with 1000 workers or more.

In rows 2 to 4 I report the differences in skill mix across firms of different size calculated from the whole population. I distinguish between 3 skill categories: unskilled, skilled and highly skilled. The numbers across the four columns of row 2 indicate that the percentages of unskilled workers in large and small firms are very similar. Row 3, however, shows that there is a slight decrease in the percentage of skilled workers (with an apprenticeship qualification) across categories, but, as shown in row 4, there is a substantial increase of highly skilled workers (with an academic degree). This indicates that at the upper end of the skill distribution, larger plants tend to hire on average higher quality workers than smaller plants.

In rows 5 to 9 we look at the skill composition across size categories using the workers in our sample. The information in the sample is more detailed and I can disaggregate the 3 education groups in 5 education sub-groups: unskilled, semi-skilled, workers with an apprenticeship qualification, with a polytechnic degree and finally with a university degree. The picture gathered from looking at rows 5 to 9 is quite similar to the one from rows 2 to 4. The proportion of workers holding a polytechnic or a university degrees is much higher in large firms. Moreover in the

[15] In this chapter I will loosely use the terms firm, plant and employer interchangeably to indicate the establishment.

Table 6.1: Composition by Size Category

		1-19	20-99	100-999	1000+	Total
1	Number of observations	26.71	22.61	29.57	21.11	324865
2	proportion unskilled in plant's workforce	30.18	31.32	32.92	31.71	31.59
		(29.83)	*(23.64)*	*(20.61)*	*(15.47)*	*(23.15)*
3	proportion of skilled in plant's workforce	67.17	64.67	61.07	57.75	62.74
		(30.28)	*(23.56)*	*(19.41)*	*(14.29)*	*(23.04)*
4	proportion highly skilled in plant's workforce	2.69	4.02	6.01	10.54	5.68
		(11.20)	*(11.16)*	*(11.12)*	*(12.28)*	*(11.75)*
5	unskilled	27.63	27.04	30.13	15.2	11.14
6	semi-skilled	28.7	24.62	28.12	18.57	6.55
7	with apprenticeship	32.99	24.36	26.4	16.25	68.86
8	fachochschule	17.49	19.49	31.87	31.15	4.54
9	university	15.75	16.41	31.66	36.18	8.92
10	tenure	2.21	2.64	3.28	4.22	3.05
		(2.56)	*(2.84)*	*(3.18)*	*(3.53)*	*(3.12)*
11	average no. jobs	2.63	2.58	2.34	1.88	2.37
		(2.19)	*(2.07)*	*(1.80)*	*(1.42)*	*(1.93)*
12	average no. jobs by size ct of first employer	2.54	2.55	2.30	1.80	2.33
		(1.94)	*(2.01)*	*(1.92)*	*(1.51)*	*(1.90)*

Notes: Means (and proportions, rows 5 to 9) reported, standard deviations in parenthesis. The sample used includes 324,865 observations, from the year 1980 to the year 1995. Total number of workers in the sample is 34,033. Total number of plants is 63,912. Rows 2 to 4 report statistics on the composition of the firms' workforce calculated using the complete population of workers, as described in E.1. Rows 5 to 9 report the distribution of 5 education levels in the sample by size category. Row 10 reports the average tenure in years. Row 11 reports the average number of jobs held in different firms according to the firm where the worker is employed. Row 12 reports a similar statistic but according to the size of the firm where the worker was first employed.

sample, the proportion of low skilled workers decreases with size of the firm.

Row 10 shows that there are significant differences in tenure: tenure increases with firm size.[16] The numbers in row 11 also suggest that workers in larger firms are less mobile than workers in smaller firms. While the average number of jobs held by a worker in the smallest category is 2.63, it is 1.88 in the largest category. Row 12 relates the total number of jobs an individual has held to the size of the first employer. Workers who started in firms with less than 20 employees hold on average 2.54 jobs compared to workers who started in firm with 1000 employees or more who have a total number of jobs of 1.8. This suggests am inverse relationship between mobility and employer size in the first job - individuals who find a large employer at entry to the labour market have a lower mobility than individuals who start at a small firm.[17]

The reason for that could be that it is the high productivity workers who match with large firms initially, thus reducing their later mobility, or that larger firms are more likely to offer internal labour markets, thus reducing mobility. Finally, it is likely that the average worker-employer match in larger plants is better and therefore it is less likely that workers of larger plants might find advantageous outside offers. Overall, these figures indicate some substantial differences in mobility patterns across workers in firms of different size. They emphasize the importance to relax the assumption of exogenous mobility when investigating firm size differentials.

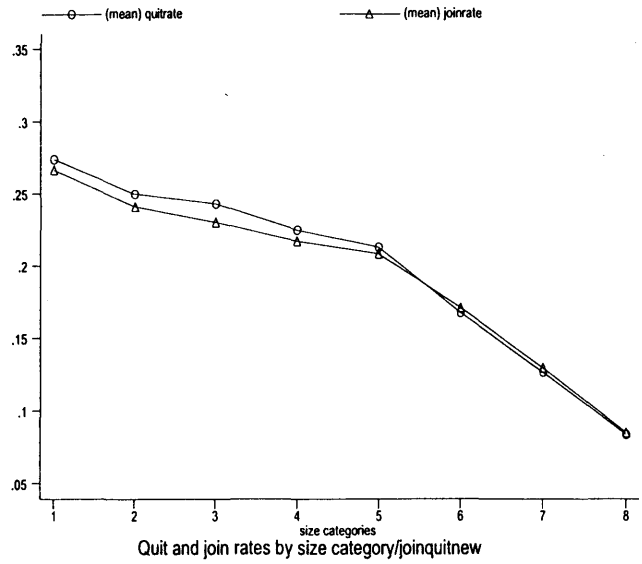
I now investigate mobility patterns in more detail. Figures 6.1 and 6.2 display the separation rates and the joining rates of workers from and to differently sized firms, where the latter figure (6.2) reports separation rates separately for unskilled, skilled and graduate worker.[18] The graphs show a clear relationship between establishment size and worker turnover, with both separation rates and joining rates decreasing with the size of the establishment. Less than 10% of the observed separations and new acquisitions take place in plants with more than 1,000 employees. This

[16]A t-test on the figures in row 10 shows that the differences are significant at the 1% level.

[17]Unreported statistics show that the average size of the first employer for workers who only hold only one job is 2,556, while for workers who hold 5 jobs or more it is 649.

[18]The dataset does not directly distinguish between quits and layoffs. I did try to distinguish between layoffs and quits using information on time spent out of the labour market, i.e. I assume that workers that are unemployed between spells have been laid off. However, it is not clear that workers, who decide to quit, would not spend time out of work to find a better match. Thus in the end I decided not to use this distinction in this analysis.

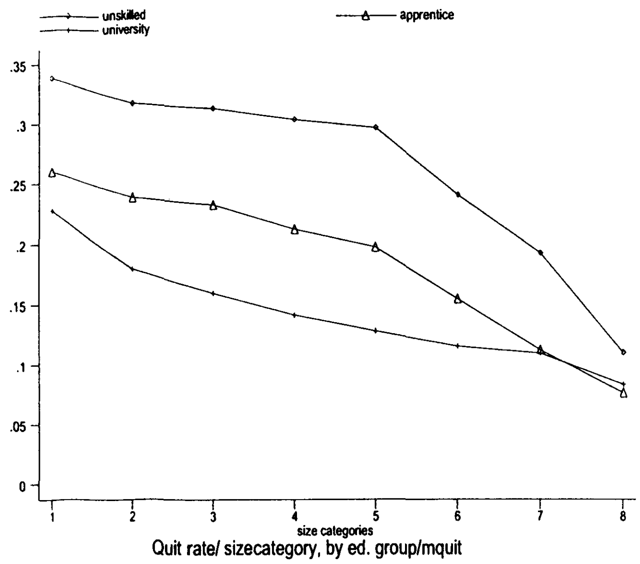
Figure 6.1: Mobility Rates across Size Categories



pattern is consistent across different education groups (figure 6.2). The figure shows that mobility is highest among unskilled workers, and lowest among skilled workers. However, quit rates converge significantly with firm size across skill groups. A possible interpretation of this is that lower skilled workers, relative to highly skilled workers, are more likely to find a good match in larger firms. I will come back to this below when I analyse wages.

Table (6.2) illustrates mobility across differently sized employers. For ease of exposition, I only distinguish between 3 size classes, less than 100 employees, between 100 and 1,000 and more than 1,000. As shown in the bottom right corner of the table, I observe 56,964 separations in the sample between 1980 and 1995. Of these 37,041, i.e. 65.03 %, are separation from firms with 100 employees or less (row 1 column 4), 25.24% (row 3 column 4) from firms with 100 to 1,000 employees, and only 9.74% (row 5 column 4) from large firms with 1,000 employees or more. Indeed row 1 shows that most of the mobility takes place among smaller plants: of the 37,041 separations from small plants 26,148, i.e. 70.59% find a new job in a firm of the same size (row 1 column 1), while only a small percentage (7.12%) finds a job in a large firm (row 1 column 3). The percentage of mobility to small from big employers is small, 2611 (row 3 column 1), and even less is the number of transitions from big plants to jobs with a similar sized employer: only 1,238.

Figure 6.2: Quit rates across Size Categories, by educational group



Our results are consistent with evidence from many countries that matches of workers to jobs in larger firms are generally considerably more stable than in smaller ones (OECD, 1993) and with previous empirical results from German data.[19]

In Table 6.3 I analyse the wage gains and losses from moving across firms of different sizes. As in all the wage analysis I restrict my sample to unskilled and skilled workers, whose wages are not affected by censoring problems.[20] I distinguish between three size categories, less or equal to 100 employees, 100 to 1,000 employees, and more than 1,000. The figures show that the wage gains from mobility across firms of the same size category are remarkably stable across categories, and they amount on average to $6-7\%$. There are large gains from mobility from small to larger firms, and significant losses from mobility from larger to smaller firms. The wage increase of those who move from a small plant to a big plant is 18% whereas those who move from a big plant observe on average a wage loss of 0.5% when they move to medium sized plants and a wage loss of 5.11% when they move to small

[19]Schasse (1991) shows that tenure tends to increase with firm size using the first four waves of the German household Panel collected between 1984 and 1987. Frick (1994), using 1988 micro data from all sectors of the German economy excluding agriculture and forestry, shows that quit rates and dismissal rates are, ceteris paribus, lower in larger than in smaller firms.

[20]When analysing the same figures for graduates in the first 4 years spent in the labour market, the gains from changes across firms within the same size categories are very similar as in table 6.3. However, in the case of graduates we never observe a wage loss, but we do observe smaller gains when workers move from larger to smaller firms

Table 6.2: Mobility between size classes

	to<=100	to 101-999	to >=1000	Total
From <=100	26148	8255	2638	37041
	70.59%	*22.29%*	*7.12%*	*65.03%*
From 101-999	7918	4693	1765	14376
	55.08%	*32.64%*	*12.28%*	*25.24%*
From >=1000	2611	1698	1238	5547
	47.07%	*30.61%*	*22.32%*	*9.74%*
Total	36677	14646	5641	56964
	64.39%	*25.71%*	*9.90%*	

Notes: Total number of observations is 324,865. Total number of separations observed in the sample 56,964. Figures reported are frequencies. In italics the table reports in columns 1 to 3 the proportion of separations in the cell relative to the total separations in the row (e.g. in the top left cell $26,148/37,041$ = 70.59%). In column 4, the table reports in italics the proportion of separations in the cell relative to the total separations in the column (e.g. in the top right cell: $37,041/56,964$ = 65.03%

Table 6.3: Wage gains and losses from mobility between size classes

	to<=100	to 101-999	to >=1000	Average
From <=100	6.60	12.62	18.21	8.73
	(33.44)	*(33.47)*	*(34.30)*	*(33.69)*
From 101-999	1.72	6.78	13.16	4.61
	(34.15)	*(32.17)*	*(31.61)*	*(33.47)*
From >=1000	-5.11	-0.52	6.33	-1.61
	(37.03)	*(31.21)*	*(28.54)*	*(34.16)*
Average	4.81	9.51	14.59	
	(33.99)	*(33.12)*	*(32.83)*	

Notes: Means of percentage wage gains reported, standard deviations in parenthesis. The sample used includes only unskilled and skilled workers, whose wages are never right censored. This sample includes 285,774 observations, from the year 1980 to the year 1995. Total number of workers in the sample is 29,454, of which 6,020 are unskilled and 23,434 are skilled. Total number of plants is 59,326. The total number of separations observed is 52,536. Of which 35,274 from small firms (of which 25,069 to small firms 7,774 to medium size firms and 2,431 to large firms); 12,897 from medium sized firms (of which 7,365 to medium, 4,080 to small and 1,452 to large); 4,365 from large firms (of which 814 to large; 1,299 to medium and 2,252 to small) plants. In general those who move to a big employer, independently from the size of the previous plant, experience an increase of 15%, while those who move to a small employer 5%.

Again, these differentials may be due to match quality - bad workers move to smaller firms, while good workers move to larger firms. In unreported analysis I investigated this issue in more detail. First, I looked at the relative wage level pre and post transition of workers who move across size categories and of those who move within the same categories. I find that workers who leave large firms to move to smaller firms are always the ones with the lowest wage in their size class. The wage levels of workers who move from small to larger plants are the highest in the size class but are still lower than those of workers worked at a large plants. This evidence confirms the presence of sorting, i.e. that high ability workers go to larger plants.

6.6 Results

This section presents the results of the empirical analysis. I start by following the traditional literature on firm size-wage effects. I first estimate OLS level regressions controlling for observed firm and individual characteristics, then I conduct longitudinal analysis using fixed effects method. I finally depart from the traditional literature and estimate the size coefficient controlling for unobserved firm and worker fixed effects, the impact of non-random mobility choices and finally for the possible endogeneity of firm size.

6.6.1 OLS results

Table 6.4 reports the estimate of a pooled OLS regression on the sample of unskilled and skilled workers.[21] Column 1 shows the unconditional size-wage differential in our sample.[22] This amounts to 4.37% and is in line with previous estimates for the German labour market. In column 2, I control for industry effects; even within industries the size wage elasticity is an economically significant 3.93%. Finally in

[21]The results for university graduates are reported in the Appendix.
[22]I include region and year dummies.

Table 6.4: Level estimates of size effects
(OLS estimates of Equation 6.1)

	(1)	(2)	(3)	(4)	(5)
ln(size)	0.04366	0.03930	0.04155	0.03590	0.03501
	*(0.00085)****	*(0.00091)****	*(0.00092)****	*(0.00088)****	*(0.00095)****
semiskilled				0.06072	0.05904
				*(0.00482)****	*(0.00482)****
with apprenticeship				0.18699	0.17823
				*(0.00380)****	*(0.00384)****
experience				0.07259	0.07241
				*(0.00134)****	*(0.00133)****
$experience^2$				-0.06112	-0.06125
				*(0.00229)****	*(0.00227)****
$experience^3$				0.01966	0.01972
				*(0.00111)****	*(0.00110)****
tenure				0.02450	0.02393
				*(0.00123)****	*(0.00123)****
$tenure^2$				-0.03876	-0.03772
				*(0.00259)****	*(0.00258)****
$tenure^3$				0.01595	0.01549
				*(0.00145)****	*(0.00145)****
plant's % skilled workers					0.00078
					*(0.00005)****
plant's % high skilled workers					0.00230
					*(0.00024)****
Observations	270271	270271	270271	270271	270271
Adjusted R-squared	0.239	0.287	0.314	0.448	0.452

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for workers in the same firm. The dependent variable is log real daily wage deflated using the 1995. Column 1 includes 15 year dummies and regional dummies. Column 2 additionally includes industry dummies. Column 3 adds occupation dummies. Columns 4 and 5 include year, region, industry and occupation dummies. * significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level. *** significantly different from zero at the 1 percent level.

Table 6.5: Sensitivity analysis

	(1)	(2)	(3)	(4)
ln(size)	0.03501	0.03452	0.03338	0.03142
	*(0.00095)****	*(0.00100)****	*(0.00103)****	*(0.00074)****
semiskilled	0.05904	0.06006	0.04907	0.05806
	*(0.00482)****	*(0.00494)****	*(0.00554)****	*(0.00464)****
with apprenticeship	0.17823	0.17744	0.15378	0.16716
	*(0.00384)****	*(0.00396)****	*(0.00432)****	*(0.00392)****
experience	0.07241	0.07057	0.06694	0.06906
	*(0.00133)****	*(0.00137)****	*(0.00156)****	*(0.00128)****
$experience^2$	-0.06125	-0.05956	-0.05455	-0.05936
	*(0.00227)****	*(0.00231)****	*(0.00258)****	*(0.00215)****
$experience^3$	0.01972	0.01926	0.01707	0.01933
	*(0.00110)****	*(0.00112)****	*(0.00121)****	*(0.00103)****
tenure	0.02393	0.02539	0.02894	0.02274
	*(0.00123)****	*(0.00125)****	*(0.00141)****	*(0.00116)****
$tenure^2$	-0.03772	-0.03871	-0.04272	-0.03384
	*(0.00258)****	*(0.00260)****	*(0.00285)****	*(0.00243)****
$tenure^3$	0.01549	0.01563	0.01699	0.01369
	*(0.00145)****	*(0.00146)****	*(0.00156)****	*(0.00135)****
plant's % skilled workers	0.00078	0.00075	0.00084	0.00056
	*(0.00005)****	*(0.00006)****	*(0.00006)****	*(0.00005)****
plant's % high skilled workers	0.00230	0.00219	0.00249	0.00146
	*(0.00024)****	*(0.00026)****	*(0.00024)****	*(0.00021)****
past growth		0.01200	0.01372	4.22657
		(0.00208)***	(0.00233)***	(0.04846)***
5 to 10 years old			0.00987	
			(0.00385)**	
older than 10 years			0.00823	
			(0.00396)**	
Observations	270271	255612	190277	270271
Adjusted R-squared	0.452	0.452	0.421	0.496

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for workers in the same firm. The dependent variable is log real daily wage deflated using the 1995 German Consumer Price Index. Columns 1 to 5 include 15 year dummies and regional dummies. Columns 1 to 3 additionally include industry dummies and occupation dummies. Column 4 includes industry and occupation dummies at a more detailed level. * significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level. *** significantly different from zero at the 1 percent level.

column 3, I additionally include occupation dummies to account for possible compensating differentials between large and small employers; the estimated coefficient remains virtually unchanged. Column 4 controls for observable workers' characteristics, education, experience and tenure. These alone explain 13% of the row size differential.[23] The coefficient on size is still a significant 3.5%. This result seems to suggest that although differences in observed workers' quality are relevant in explaining the size wage gap they are not the whole story.

In column 5 I investigate whether the firm size wage gap might be explained by differences in educational composition across plants of different size. The skill mix of the establishment is a variable usually not available in data sets used for the analysis of size wage differentials. The coefficients on both the percentage of skilled workers and university graduates is positive and significant with the coefficient on the percentage of university graduates being significantly larger than the coefficient on the proportion of skilled workers. However, the coefficient of size has not significantly decreased. Size is not a proxy for differences in skill composition.

In table 6.5 I check the robustness of the estimates reported in Table 6.4. In column 1 I report the results of the preferred specification (column 5 of table 6.4). A characteristic of larger firms paying higher wages is that larger firms are more successful, and have experienced larger past growth. A unique feature of the data is that I observe the size of each establishment any worker has ever been employed at between 1980 and 1995. I can therefore construct a variable on past establishment growth and add it to the regressors. The estimates reported in column 2 show that past growth of the plant, measured as the difference $ln(employment)_{t-1} - ln(employment)_{t-2})$ has a significant positive effect on wages, but this seems orthogonal to the effect of plant size, which remains virtually unchanged.

In column 3 I investigate whether, as suggested by Brown and Medoff, *"the size-wage premium is really a relationship between employer age and wages"*, by including age as categorical variable; plants that have been in business less than 5 years ('young' businesses), between 5 and 10 ('adult' businesses) and more than 10 years ('old' businesses).[24] According to my results, this is not the case: conditional

[23]The 13% is calculated as follows: the ratio of the differences in the coefficients in column 3 and column 4 to the coefficient in column 1, i.e. (0.04155 – 0.03590)/0.04366

[24]Since the age variable is censored I use observations for which I can calculate the exact age,

on workers's characteristic the plant's skill composition and size, the age effect is significant, but it does not affect the significance and the magnitude of the size coefficient.[25] Finally in column 4 I check the robustness of the results to using much more detailed industry and occupation classifications, the results show that the size elasticity is still more than 3%.

From these two tables (6.4 and 6.5 I can conclude the following. Firstly, the size coefficient is robust to the inclusion of observable plants' and and workers' characteristics, the effect of age is significant, but does not affect the significance of the size variable; the effect of past plant growth is strongly significant but does not affect the size coefficient. The inclusion of observable workers' and firm characteristics explain 20% of the row size wage differential.[26] I now proceed to investigate the role of unobservable plant and workers' characteristics on the size wage gap.

6.6.2 Longitudinal estimates

A problem with simple cross sectional estimates is that firm size may be correlated with individual specific heterogeneity. One way the literature has addressed this problem is to estimate difference equations, or to condition on individual fixed effects. In column 2 of table 6.6 I present results of first difference equation of our preferred specification (corresponding to column 5 in table (6.4), which I report in column 1 of table 6.6 for convenience.

In column 2 the size coefficient drops to about 0.022. A first possible criticism is that if the variable size is measured with error the reported estimates are affected by attenuation bias and one should prefer to use the fixed effect estimator. The two estimators are asymptotically consistent, but since fixed effect estimates use both first and longer differences, they are less affected by measurement error than first

i.e. firms that were recorded starting business later than 1977. The dummy variable 'old' includes firms for which the age variable is left censored –they were already in business in 1977 – and for which I only know that they have been in business for more than 10 year. I experimented with alternative specifications; e.g. I have included age as a dummy variable equal to 1 for plants older than 10 years, as logarithmic or cubic polynomial. The size coefficient is never affected by the inclusion of controls for age.

[25]The significance of the age coefficient is at odds with recent results by Brown and Medoff who find that higher wages paid by established firms are completely explained by observable characteristics of their workers. This might be due to the high proportion of censored observations in my sample: for 51% of the regression sample I can only say that they are older than 10 years, because their 'birth' variable is left censored.

[26]$20\% = (0.04366 - 0.03501)/0.04366$

Table 6.6: Longitudinal estimates of size effects

	(1)	(2)	(3)	(4)	(5)
ln(size)	0.03501	0.02178	0.02933	0.01192	0.01943
	(0.00095)***	(0.00065)***	(0.00061)***	(0.00100)***	(0.00159)***
semiskilled	0.05904				
	(0.00482)***				
with apprenticeship	0.17823				
	(0.00384)***				
experience	0.07241	0.02918	0.06562	0.04931	0.05329
	(0.00133)***	(0.00242)***	(0.00166)***	(0.00674)***	(0.00755)***
$experience^2$	-0.06125	-0.07834	-0.06140	-0.04796	-0.04338
	(0.00227)***	(0.00263)***	(0.00200)***	(0.00214)***	(0.00239)***
$experience^3$	0.01972	0.02996	0.01925	0.01682	0.01376
	(0.00110)***	(0.00120)***	(0.00095)***	(0.00096)***	(0.00106)***
tenure	0.02393	-0.01827	0.00522	-0.01328	-0.00656
	(0.00123)***	(0.00120)***	(0.00100)***	(0.00645)**	(0.00711)
$tenure^2$	-0.03772	0.03571	-0.01521	-0.00096	-0.00294
	(0.00258)***	(0.00252)***	(0.00212)***	(0.00192)	(0.00235)
$tenure^3$	0.01549	-0.01581	0.00678	0.00116	0.00039
	(0.00145)***	(0.00137)***	(0.00117)***	(0.00099)	(0.00121)
plant's % skilled workers	0.00078	0.00033	0.00036	0.00010	-0.00003
	(0.00005)***	(0.00004)***	(0.00004)***	(0.00005)**	(0.00008)
plant's % high skilled workers	0.00230	0.00124	0.00139	0.00004	0.00036
	(0.00024)***	(0.00016)***	(0.00017)***	(0.00015)	(0.00025)
Observations	270271	241625	270271	191522	270271

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for workers in the same firm. All regressions include include year and occupation dummies. Column 1 replicates column 5 of Table 6.4. Column 2 reports First Difference and Column 3 Fixed Effects estimates of equation 6.1. Columns 4 and 5 report within-firm first difference (column 4) and fixed effects (column 5) estimates of equation 6.1. * significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level. *** significantly different from zero at the 1 percent level.

difference estimates (Griliches and Hausman, 1986).

Therefore in column 3, I estimate a fixed-effect regression rather than a first-difference regression: the coefficient is significantly larger,[27] thus suggesting the presence of some measurement error. These estimates might be interpreted as suggesting that unobserved individual fixed effects explain between 20% and 38% of the size gap of column 1.

However, the estimates of column 2 and 3 do not condition on individual mobility choices. Thus, estimation in columns 2 and 3 is based on workers who change firms and workers who remain attached to the same plant.

Unlike studies of inter-industry wage differential or of studies of size wage differential that only have categorical measures of plant size, I can use the longitudinal variation in the continuous measure of plant size and estimate within-plant first difference equation. In column 4, I report the estimates of first differences on 'stayers', which control not only for individual effects but also for the firm and match specific components. Now the size coefficient drops significantly, and reduces to less than one half compared to the level specifications, to 0.012. This indicates that both match quality and individual heterogeneity lead to upward biased parameter estimates in simple OLS regressions. As I did for column 2, I also report fixed effects estimates that should alleviate measurement error problems, the size elasticity now rises to 19.4%. However, these estimates are still affected by selection bias: workers that stay in the current jobs are workers for which the outside wage offer does not exceed the current wage and the sample coefficient estimated on the sample of 'stayers' will be biased.

6.6.3 Correcting for non-random mobility

As shown in section 6.5, mobility is unlikely to be random. In this section I follow the approach described in section 6.3 to correct for the bias induced by non-random mobility in the estimates of equation 6.6. I implement the following two-step procedure: in the first step I estimate a reduced-form probit of the probability of staying with the firm, predict the inverse Mill's Ratio which I then include in the second-step in an OLS regression of within-plant wage growth, correcting the standard errors using

[27] A chi square test reject the null that the coefficients on size are the same across the two specifications

Table 6.7: Mobility equation and corrected longitudinal estimates

	(1)	(2)	(3)
	probit	FD within	FE within
ln(size)	0.02352	0.01556	0.02101
	*(0.00060)****	*(0.00110)****	*(0.00126)****
experience	-0.00808	0.03781	0.04791
	*(0.00268)****	*(0.00674)****	*(0.00801)****
$experience^2$	0.00180	-0.03500	-0.03096
	*(0.00049)****	*(0.00251)****	*(0.00210)****
$experience^3$	-0.00010	0.01093	0.00884
	*(0.00003)****	*(0.00100)****	*(0.00092)****
tenure	0.10625	-0.00426	-0.00363
	*(0.00297)****	*(0.00570)*	*(0.00763)*
$tenure^2$	-0.01449	-0.01332	-0.00632
	*(0.00072)****	*(0.00266)****	*(0.00193)****
$tenure^3$	0.00061	0.00628	0.00194
	*(0.00004)****	*(0.00122)****	*(0.00105)**
plant's % skilled workers	0.00073	0.00011	-0.00002
	*(0.00006)****	*(0.00005)***	*(0.00006)*
plant's % high skilled workers	0.00132	0.00012	0.00033
	*(0.00025)****	*(0.00020)*	*(0.00019)**
$\widehat{lambda}$		-0.01571	-0.00139
		*(0.00542)****	*(0.00057)***
semiskilled	-0.04853		
	*(0.00723)****		
apprentice	0.01757		
	*(0.00495)****		
age	0.01303		
	*(0.00077)****		
married	0.01539		
	*(0.00342)****		
with children	0.00465		
	(0.00651)		
1 exogenous job loss	-0.11118		
	*(0.00477)****		
2 exogenous job losses	-0.15369		
	*(0.01226)****		
3 exogenous job losses	-0.14878		
	*(0.02389)****		
4 exogenous job losses	-0.19064		
	*(0.04532)****		
5 exogenous job losses	-0.25342		
	*(0.10957)***		
6 exogenous job losses	-0.18581		
	*(0.00807)****		
Observations	234320	166597	234320

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for workers in the same firm. All regressions include include year and occupation dummies. * significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level. *** significantly different from zero at the 1 percent level.

block bootstrapping to correct for the fact that the inverse Mill's Ratio is estimated in the first step.[28] The exclusion restrictions that allow identification are: age, which is assumed to affect mobility choices but, conditional on experience and tenure, not to affect wages. I also include the number of time a worker has previously lost his job for exogenous reasons, i.e. because of plant closure. The reason for including this variable is that every time a worker is displaced, he loses his search capital and therefore will find himself in the lower part of the wage distribution. Thus, I expect that the more often a worker has been previously displaced, the more likely he is to receive better outside offers and quit the current employer.[29] Finally, I include two dummy variables for the marital status of the worker and for whether he has children, which again are assumed not to be correlated with the error term in equation 6.6. The results of estimating this reduced form probit are reported in column 1 of Table 6.7, where I report the marginal effects from the probit equation. The results show that workers of larger plants are more likely to stay in the same job, as are married men. Having children does not significantly affect the decision to stay with the same plant. The dummies for the number of previous exogenous displacements has, conditional on actual experience and tenure, both a negative coefficient. Skilled workers, older workers and workers with large actual experience and tenure are more likely to stay in the same job, as are workers employed in plants with a large proportion of skilled workers. In column 2 of Table 6.7 I report the estimates of the within wage growth equation correcting for non-random mobility. The inverse Mill's ratio coefficient is significant and negative. The estimates show that controlling for endogenous mobility the estimated size coefficient is still significant and is actually larger than in the previous table, where I do not control for non random mobility. As in the previous table, however we also estimate a fixed effects equation that might be more robust to the presence of measurement error. The result show that controlling for non random mobility and measurement error, the size coefficient

[28] In the block bootstrapping procedure I treat each worker-employer combination as a different sampling unit. This allows for heteroscedasticity of unknown forma and for serial correlation.

[29] A similar approach used in the literature to control for endogeneity of mobility has been to use a sample of displaced workers (see for example Gibbons and Katz (1992) for the estimation of interindustry wage differentials and Dustmann and Meghir (2004) on estimating returns to experience and tenure. I preferred not to adopt this approach here, since smaller firms are more likely to close down and therefore selecting the the sample to displaced workers also meant restricting the sample to smaller plants. Also I would still face a problem of selection when using the wage growth after displacement.

Table 6.8: Size elasticities across education groups:summary table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				UNSKILLED				
ln(size)	0.057	0.048	0.030	0.041	0.008	0.014	0.009	0.014
	*(0.002)****	*(0.002)****	*(0.002)****	*(0.002)****	*(0.004)**	*(0.007)***	*(0.005)**	*(0.005)****
				SKILLED				
ln(size)	0.039	0.035	0.022	0.028	0.011	0.016	0.012	0.017
	*(0.001)****	*(0.001)****	*(0.001)****	*(0.001)****	*(0.001)****	*(0.002)****	*(0.002)****	*(0.002)****
				HIGH SKILLED				
ln(size)	0.037	0.031	0.013	0.019	0.007	0.011	0.008	0.012
	*(0.002)****	*(0.002)****	*(0.003)****	*(0.003)****	*(0.003)***	*(0.005)***	*(0.003)****	*(0.004)****

Notes: Robust standard errors in parentheses, estimated allowing correlation between unobservables for workers in the same firm. All regressions include include year and occupation dummies. The sample used in the regression only includes the first 5 years of labour market experience of all education groups. The first column of the table reports results from a pooled level regression where I only include *ln(size)*, region and time dummies. In column 2 I include observable plants' and workers' characteristics as I did in column 5 of table 6.4. Column 3 and 4 report longitudinal estimates, first difference (column 3) and fixed effects (column 4) within and across firms. Column 5 reports within firm first difference estimates and column 6 fixed effects estimates. Finally, columns 7 and 8 report within firm first difference and fixed effects estimates, respectively, that correct for non random mobility. * significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level. *** significantly different from zero at the 1 percent level.

is now 2.1%.[30]

6.6.4 Firm size and education

In the results presented I only included unskilled and skilled workers and I excluded university graduates because of the above mentioned censoring problem. In this section I report results for the graduates and I distinguish between individuals with different educational background according to the classification 'unskilled', 'skilled' and 'graduates'. Given the problem of censoring I restrict the analysis for university graduates to the first 5 years in the labour market and to make the estimates comparable across the three education groups I restrict the sample of unskilled and skilled workers accordingly.

Some of the previous literature has established that returns to education differ across different size categories. In particular, Garen (1985) has formalized a theoretical model which has the implication that large plants rely more heavily on external indicator of ability, such as schooling, to assess workers' productivity. This would

[30]There might still be another source of bias in my estimates of the size elasticity. Idiosyncratic shocks may be positively correlated with both wage growth, and growth in the size of the firm, thus leading to an upward bias. One possible approach to correct for the correlation between size growth and the idiosyncratic shocks is to use as instruments for the difference in log size lagged values of plant size. I did try to use this approach and in particular I use lagged value of size as a continuous variable and as a spline with nodes at 5, 20 and 100 employees, values of size at which relevant employment dismissal laws and implementation of work councils become more stringent. However, the Sargan test always rejected the validity of the instruments.

imply that returns to schooling increase with plant size. The empirical results, however, are ambiguous.

Previous empirical findings for Germany (Gerlach and Schmidt, 1990) have shown that the returns to schooling are positively correlated with firm size. Gerlach and Schmidt claim that this finding is supportive of Garen's model; they also reports that previous studies (Bruederl and Preisendoerfer, 1986) do not find significant differences in returns to schooling between small and large plants. Findings for other countries are not clear cut. Brown and Medoff, Idson and Feaster and Oi report a tendency for the wage differential to decline with skill levels. Main and Reilly (1993) find that the estimated returns to education are highest in "small" plants, but that the differences in the estimated returns to education across different size classes for the UK are not significant. Finally, the study by Albaek et al. (1998) on the Nordic countries finds no evidence that reward to formal education vary with size of the plant and descriptive evidence shows that large plants do not seem to attract workers with higher level of education relative to small plants.

To investigate the relationship between wages and establishment size for individuals in different educational categories, I estimate a modified version of column 5 of table (6.4) for skilled, unskilled and university workers.[31] The first two columns presents results from simple OLS regressions. The numbers indicate that there is a significant difference between the wage size differentials between graduates, skilled and unskilled workers: with the size gap being significantly larger for unskilled workers, whether or not we control for firms' and workers'characteristics (column 2) or not (column 1). The next two columns present first difference equations (row 3) and fixed effects estimates (column 4) for all workers. This eliminates the fixed individual specific effect, but not the innovation in the match quality. The size of the coefficient is reduced, but there is still a significant difference between graduates, skilled and unskilled workers.

In the fifth and sixth columns, I present within-firm difference and fixed effects estimates. The size wage differential reduces even further, which is due to the elimination of the firm and match specific components. Now the firm size differentials are practically the same for skilled and unskilled workers. Columns 7 and 8 report

[31]I only include a quadratic in experience and tenure, since I only consider the first 5 years in the labour market.

the first difference (column 7) and fixed effects estimates (column 8) where I control for non-random mobility.[32]

These results suggest that unskilled workers are more likely to find a good match in larger firms than skilled workers, leading to a larger correlation between μ_{ij} and $S_{j(i,t)t}$ in (6.4) and consequently a larger bias. This would imply that the difference in mobility between skilled and unskilled workers is smaller in larger firms, since the difference in the match quality is likewise smaller. This is exactly what figure (6.1) suggests - while there is a substantial difference in mobility between skilled and unskilled workers in small firms, but there is little difference in larger firms.

6.7 Conclusions

This chapter studies size wage differentials using longitudinal administrative data from the IAB data for Germany for the 1980-1995 period.

The underlying model is one that encompasses comparative advantage and the existence of true firm size effects. The objective of the chapter is to estimate size wage elasticities that are not affected by unobserved heterogeneity in workers' ability, worker-employer matches and firm fixed effects. I achieve this by estimating within firm wage growth equation and controlling for the endogeneity of mobility choices of workers. Identification relies on the exogeneity of the instruments in the mobility equation: age, marital status, and number of previous displacements.

The empirical findings show that controlling for observed workers' and firms' characteristics can explain about 20% of the observed size wage gap. Unobserved firm, match and workers' effects account, once we control for the presence of measurement error and non random mobility for an additional 32% of the size wage gap, i.e. we explained about half of the size wage differential.[33] According to our fixed effects estimates gap of 2.1% remains unexplained.

I also show that the estimated size wage gap is robust to the inclusion of firms' past success and firms' age.

Finally, I show that in the level equation this firm size advantage decrease with

[32]The complete set of estimates for the three education groups are reported in tables E.2; E.3 and E.4 in appendix E.3

[33]These figures are calculated as follows: 20%=(0.044-0.035)/0.044 and 32%(0.035-0.021)/0.044.

the educational level. However, in the longitudinal analysis, I find that the size wage elasticity does not vary significantly across education groups. This results are at odds with models that predict that large firms tend to reward more education than less directly observable measure of ability.

Chapter 7

Summary and Conclusions

The purpose of this final chapter is to review the main findings, policy conclusions and limitations of this thesis. For each chapter, I summarize the main findings, I then delineate some points deserving further attention, suggest some ideas for future research and policy conclusions.

In Chapter 2 I looked at the role of differences in share ownership structure for explaining differences in productivity. The main contribution is to exploit the longitudinal nature of the data to investigate a long-debated issue in the economic literature. Does the separation between ownership and control matter for firm performance? Most of the previous literature has analysed the effects of this separation on market value. I know of only two previous studies (Curcio, 1994 and Nickell et al., 1997) that have looked at the relationship between ownership and productivity growth in the UK. To the best of my knowledge the analysis in this chapter is the first to look at the effects on productivity levels.

The findings show that, as predicted by principal-agent models a higher concentration of ownership guarantees a higher efficiency in the firm. I find that this effect is stronger if financial institutions are among the largest shareholders.

The study presents a number of limitations and is open to improvements and extensions. I discuss them in turn. The first criticism that could be raised is that in the analysis I do not explicitly control for other corporate governance mechanisms that can affect firm's productivity. According to agency theories of the firm, when shareholders appoint agents to the management of assets, these managers will act in the interest of their principals only as far as this behaviour is beneficial to themselves. Market structure pressures and, more generally, the environment where the firm operates are important factors in determining the extent to which direct monitoring by shareholders can be substituted by alternative discipline devices (Fama, 1980). In particular, I do not control for the firm financial condition and for the competitive environment in which the firm operate.[1] For example, debt financing matters, as increased debt reduces free cash flow and so limits managerial discretion (Jensen, 1986). Also I cannot control for other firm characteristics such as age and multinationality because of lack of information in the data. The first extension of this chapter, therefore, would be to enrich the available information in the data to account for these factors.

The second area that I believe deserves further analysis is whether share ownership affects productivity and market value differently. This analysis would constitute the missing link between the analysis of this first chapter of the thesis and the existing financial literature on ownership and market value.

A third promising extension is to match to the ownership data information with patenting activity. Indeed, theories have focused on two main effects of the separation of ownership from control: on efficiency and effort (Leibenstein, 1987 and Laffont and Tirole, 1986 and on innovative activity Aghion et al., 1997). Using the matched data would allow me to test the predictions of these latter class of models and to take into account both the effect of ownership structure both on productivity level, i.e. the short run effect on efficiency and effort, and on productivity growth, i.e. the effect on innovative activity. This type of analysis would contribute to the ongoing debate on the short-termism of financial institutions that the current (static) analysis on firm efficiency does not take into account.

Notwithstanding its limitations, the findings of this chapter have several implications. The findings contribute to the corporate governance debate in both the US and the UK, which has, in recent years, focused on the potential for institutions to take a more active role in the governance of corporations. At the same time, this field of research is important not only in shaping future regulations in the UK or US, but also for policy makers in countries where the stock market is not as developed (e.g. transition economies) and for countries that need to reform their pension

[1] However, I do check the robustness of the results to the inclusion of industry time interaction dummies.

systems (e.g. in continental Europe). The findings suggest that one of the public policy objectives should be to make corporate governance by institutional owners as effective as possible. Indeed, the estimates do not support the common view that the high presence of financial institutions as large shareholders is detrimental for productivity. In particular, these findings speak against excess regulation or legal restrictions on stock ownership that raise the cost of participation of institutions in corporate governance, which prevent them from building significant stakes in individual corporations.

The third chapter uses a newly available dataset to identify domestic MNEs in a large scale UK plant level productivity dataset. The chapter shows that the productivity leadership of US owned plants relative to all other multinationals, British and foreign, remains after controlling for industry and observable firm characteristics; thus qualifying previous findings of Doms and Jensen. Secondly, we find that, except for the US, the foreign ownership advantage in Britain is indeed by and large an MNE advantage. For non-US foreign owned plants, multinationality explains most of the foreign advantage; once we control for their capital intensity they are as productive as domestic MNEs. Finally, we investigate the validity of three hypotheses on the sources of the MNE and US advantage using the longitudinal dimension of our data.

We confirm the prediction of theories of multinationals, which suggest that the productivity advantage of MNEs is to be attributed to specific firm level assets (e.g. patents, branding and know-how of production processes) which MNEs can transfer to any of their affiliates. We also find that MNEs pick the best plants in the UK. In fact, we find that the additional superiority of US firms over all other MNEs seems to be entirely driven by a particular ability of US firms to 'cherry-pick' the best British plants rather than improving the productivity of acquired plants any more than other MNEs do. Finally, we try to test whether we can find any evidence of productivity improvements due to reverse technology transfers for plants owned by British firms that start investing abroad. We do not find any significant evidence for an ex-post productivity increase for these plants. However, this result might be due to the short time series available.

Indeed, the short time series is probably a weakness of our data: we only have a 5 year panel. This, in conjunction with the unbalanced nature of the ARD panel, makes it very hard to capture long run productivity effects for the plants in the sample. The second main limitation of the study is that we do not control for a potential correlation between idionsyncratic (time varying) shocks and the multinational status of the plants. Our model only controls for correlation between MNE status and firm and plant fixed effects. This was due to the lack of valid instruments to control for this type of endogeneity. This limitation suggests that a first extension of this research might concern finding these instruments. Our results suggest a direction for the search of these instruments: the stock market value of foreign markets relative to the UK.

In fact, the relationship between FDI and stock markets is an area of research that deserves further exploration. Indeed, the 'cheap capital' view of FDI provides a plausible explanation of the US best plant effect: US MNEs, overvalued in the US stock market, and thus with access to low cost capital, might have found it more profitable to use this capital to target firms in the UK not affected by the same stock market bubble.

Finally, in this study we consider inward direct investment. The second area that we want to investigate is the outward foreign direct investment decisions of UK MNEs. Firstly, where do they invest? What are the factors that affect this decision? But also, is there any relationship between their productivity in the UK and the location of their subsidiaries? Can we find any evidence of reverse technology effects when we consider UK-US links?

The results of these projects will be complementary to the research conducted in chapter 3 in understanding the role that MNEs have for countries' productivity levels and for exchanges of knowledge flows across countries.

Chapter 4 focuses on one particular aspect of the MNEs' success: their higher innovative activity. The findings show that almost two thirds of the higher innovative outcome of MNEs is due to MNEs sharing technological knowledge within the enterprise group and with suppliers and customers more than domestic non-globally engaged firms. This therefore seems a plausible source of the firm advantage found in the previous chapter. This result points to the fact that when conducting studies on returns to innovation investments it is important to account for the utilization of investments and knowledge in other firms belonging to the MNE group. Generally, this is not been possible for lack of data.

The CIS data, despite its limitations, is useful in that it does measure the importance of knowledge flows across firms belonging to the same group. The analysis in this chapter can be extended in two different directions.

Firstly, the qualitative measures on knowledge flows across firms in the same sectors (i.e. horizontal flows across competitors), and vertical, from suppliers and customers, might be used to devise a measure of spillovers from foreign firms to domestic ones, which combines existing quantitative measures based on presence of foreign multinationals with the qualitative measures from the CIS. This would contribute to the evaluation of the usefulness of governments outlays in subsidies and incentives for foreign firms to locate and/or expand existing production in a particular region or country.

Secondly, the data contains information on the location of the agents and institutions with which a particular firm cooperates. I could exploit this information to investigate the existence and importance of knowledge flows from 'technology sourcing' from outside the boundaries of the multinationals (e.g. universities, suppliers) from technologically advanced countries, such as the US.[2] The research would contribute to identify the importance of sourcing from countries on the technology frontier. The results would have important policy implications. If the findings show a significant role for technology sourcing, then, as noted by Griffith et al. (2004a), they would suggest that policies that might induce MNE companies, in particular from EU countries, to relocate their operations and their research activity from the US back to their home countries could hinder the innovative success of these firms in that they would reduce the ability of European firms to benefit from US knowledge stocks.

Chapter 5 of this thesis matches Community Innovation survey (CIS) with production data from the ARD. The first aim is to confirm that the CIS, notwithstanding its limitation, is a valid tool for analysis. The second aim is to estimate the link between innovation and productivity growth, using a specification of the production

[2]Similar studies have been conducted mainly in the business literature (see for example the recent analysis of Criscuolo 2004) and more recently in the economic literature (see the work of Griffith et al. 2004a).

function (Klette, 1996) that rationalise different effects for product and process innovation and allows for the presence of non constant returns to scale and imperfect competition. Thirdly, I describe the innovation activity of firms using an innovation investment equation and a knowledge production function equation, which highlight the role of investment in innovation activities, outside formal R&D laboratories and, but also of external knowledge flows.

The results confirm that it is innovation output and not innovation input that affect productivity growth: product innovation, particularly when is new to the market, is positively correlated with higher TFP growth; process innovations are also positively correlated with TFP growth, but only as far as they have increased the flexibility of production, thus suggesting the presence of adjustment costs. Finally, the results also suggest that organisational change is important for TFP growth.

In the analysis of the innovation process, competition, strategic protection methods, financial support, a high level of knowledge capital within the firm and the presence of suppliers and customers as source of relevant information play an important role in the innovation investment decision.

The innovation output equation shows that, beside investment and high absorptive capacity, as proxied by internal information, the main correlates with innovation output are, for both product and process innovations, cooperation, and information from suppliers and customers.

Although I attempt to account for endogeneity of the innovation input; the choice of the instruments used for identification is subject to criticism. This is probably one of the main limitations of this study. Ideally, I would have wanted to use panel data analysis. However, the CIS innovation panel presents a number of limitations, the first one being the fact that we only have information for two waves of the survey and only for 787 firms.

In spite of its weaknesses, the chapter provides a useful framework to study innovation and its relationship with productivity growth. An immediate extension is to use a similar framework to study the link between innovation and productivity growth in the service sector, and analyse the differences between the manufacturing and the service sectors. Indeed, the CIS data seem particularly suitable for such an analysis, since they comprise a broad definition of innovation activity.

Finally, chapter 6 of this thesis uses German administrative data to investigate employer size wage differentials. The size-wage differential is a significant fraction of the overall wage inequality in several countries and across time[3] but has not been well explained by traditional theories.

The analysis of this thesis extends the available empirical literature on the firm size-wage effect in several ways. The analysis uses a very rich and detailed longitudinal dataset, that allows to control for observable workers qualities and some firm characteristics that the literature has suggested as determining the size wage differential. The panel structure of the data and the detailed information on job mobility allows to account for workers' and firms' unobserved heterogeneity controlling for endogeneity induced by non-random mobility. In particular, I use information on firm closures to construct an instrument, that together with workers' age and family characteristics, alleviates the problems generated by endogenous worker mobility.

My findings show that even after controlling for observable workers' characteristics and for occupation and industry-specific effects, a substantial wage differential remains between large and small firms and only part of the observed size wage differential can be attributed to larger firms employing workers with greater unobserved ability. Part of the remaining wage differentials is due to firms' heterogeneity and heterogeneity if worker-firm match quality. What underlies the remaining wage differential is unclear.

Since different explanations of the size wage differential may lead to different policy implications, determining the source of the wage-firm size effect is an important question for future research.

[3]Davis and Haltiwanger (1991) for example show that changes in for the period 1976 to 1985 the size-wage differentials alone account for 40% of the increase in the ninetieth-tenth percentile wage differential among US manufacturing workers.

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Appendix A

Appendix to Chapter 2

A.1 Additional details on the data and variables definition

A.1.1 Measure of ownership structure

I construct several measures of ownership structure. These identify the concentration of ownership, the type of shareholders or both. The variables that describe the concentration of ownership are:

- TOP1, the cumulative percentage of all shares held by the largest shareholder
- TOP5, the cumulative percentage of all shares held by the largest five shareholders.
- TOP10, the cumulative percentage of all shares held by the largest ten shareholders.
- BLOCK5, the cumulative percentage of all shares held in blocks greater or equal to 5%.
- HERFINDAHL, the Herfindahl index of concentration. Since I only observe the actual proportional shareholdings for the largest ten shareholders, I calculate the lower and upper bound of the Herfindahl index following a method in line with Cubbin and Leech (1983) and described in detail in the Appendix A.1.2.

identity of shareholders are:

- FININST the proportion of total identified shareholdings owned by financial institutions. This group includes pension funds, insurance companies and other institutions
- INDIV the proportion of total identified shareholdings owned by individuals.

Since I do not have information on all the outstanding equity of the firms, when I use these measures I am assuming that the distribution of ownership among shareholdings smaller than 0.25% is the same as the distribution for shareholdings larger than 0.25%. Although this might seem a strong identifying assumption, it reflects the fact that the distributions in the two groups of shareholdings are likely to be positively correlated. Alternatively, one can assume that the ownership distribution of shareholdings smaller than 0.25% is common across companies and therefore the true distribution is obtained by weighting the observed distribution and the common one.

I also introduce interaction variables:

- TOPiBIG the proportion of shares owned by the largest shareholder, if it is an individual.
- TOP5IND, the proportion of shares held by the five largest shareholders owned by individuals.
- INDPROP10, the proportion of shares held by the ten largest shareholders owned by individuals.
- TOP5INST the proportion of shares held by the five largest shareholders owned by institutions.
- INSTPROP10 the proportion of shares held by the ten largest shareholders owned by institutions.
- BLOCK5INST, the proportion of shares held in blocks greater or equal to 5% by institutions.
- BLOCK5IND, the proportion of shares held in blocks greater or equal to 5% by and by individuals

Table A.1: CDA Spectrum ownership information. Source: Bond Chennels and Windmeijer (1997)

Variables	Category	Identifying Names
Financial Institutions	Pension Funds	Annuities, Pension, Pens, Pen, PF, SF, PS, PT, SS, Superannuation, Superann, Supann, Sprnn, Retirement, Rtr bnf
	Insurance Companies	Insurance, Insur, Ins, Assurance, Assur, Life ass, Reinsurance, Rensurance, Reins
	Other Financial Institutions	Bank, Banque, Bnk, Investments, Investment, Investors, Invest, Inv, Managements, Mangement, Managers, Portfolio, Capital, Financial, Finance, Securities, Equities, Equity Growth, Trustess trust, Trst, Tstes, Tstee, Tstees, Units, Unit, Fund, Fnd, Union
Others	Non-financial Companies	Inc, Ltd, Plc, Enterprises, Corporation, Corp, Group, & Son, NV, SA, Societe, SA, BV, AG
	Private Clients of banks	Clients
	Other Institutions	Univ, Univesity, College, Council, Metropolitan Borough, London Borough, Ldn, Brgh, Corporation of London, Lord mayor,Accountant, Monetary, Sultan of Brunei, Church Commissioner, American Depository, Government of, treasury, Treasurer
Individuals	Individuals	All remaining shareholdings
Unidentified	SEPON	SEPON Ltd
	Nominees	Nominee, Nominees, Nomin, Noms, Nom

A.1.2 The Herfindahl Index of concentration and its bounds

I have constructed a measure of the Herfindahl index and its bounds following the methob used by Cubbin and Leech but modified to account for the fact that my data identifies the actual proportional shareholdings for the largest ten shareholders, the total number of shareholdings above or equal to 0.25% and thus the total holdings. I define S_i the holding of shareholder i and I rank the shareholdings in decreasing order of size as follows:

$$S_0 \leq S_1 \leq \ldots \leq S_{10} \leq S_{11} \leq S_n \leq S_{n+1} \leq S_N \tag{A.1}$$

where S_0 is the largest holding, S_10 is the tenth largest holding, i.e. the smallest for which I know the actual proportional shareholding, S_n is the smallest shareholing whose owner is identified, i.e. is above or equal to 0.25%, S_N the smallest and N is the total number of shareholders, that is unknown. I also define

$$T_N = \sum_{i=1}^{N} S_i$$

$$T_{N-n} = \sum_{i=n+1}^{N} S_i$$

$$T_{n-10} = \sum_{i=11}^{n} S_i$$

$$T_{10} = \sum_{i=1}^{10} S_i$$

and

$$P_i = \frac{S_i}{T_N}$$

If I could observe the complete distribution of holding I could calculate the Herfindahl index of concentration as follows:

$$H_{true} = \sum_{i=1}^{N}(\frac{S_i}{T_N})^2 = \sum_{i=1}^{10}(\frac{S_i}{T_N})^2 + \frac{T_{n-10}}{T_N}\sum_{i=11}^{n}(\frac{S_i}{T_{n-10}})^2 + \frac{T_{N-n}}{T_N}\sum_{i=n+1}^{N}(\frac{S_i}{T_{N-n}}) \tag{A.2}$$

Thus,

$$H_{true} = \sum_{i=1}^{10} P_i^2 + (C_{n-10} - C_{10})^2 H_{n-10} + (1 - C_{n-10})^2 H_{N-n} \tag{A.3}$$

Directly from the data I can exactly calculate the first term of the equation, C_{10} and C_{n-10}. For both H_{n-10} and H_{N-n}, I can only calculate lower and upper bounds. For H_{n-10}, the upper bound is calculated assuming that the 11th and all smaller identified shareholders have the same holding as the tenth largest shareholder; the lower bound assumes that the 11th and all smaller identified shareholders have 0.25% proportional shareholdings. Similarly for H_{N-n} I can construct an upper bound assuming that all non-identified shareholdings are 0.25% and the lower bound in the limit is 0, i.e. where non identified shares are held by infinitely many shareholders. Thus, the bounds on the Herfindahl index of ownership concentration are given by:

$$\sum_{i=1}^{10} P_i^2 + (C_{n-10} - C_{10})0.0025 < H_{true} \leq \sum_{i=1}^{10} P_i^2 + (C_{n-10} - C_{10}) P_{10} + (1 - C_{n-10})0.0025 \tag{A.4}$$

Finally, as a measure of concentration I construct the Herfindahl index of Concentration Herf, which is the average of the lower and upper bounds.

A.2 The Structure of the sample

Table A.2: Structure of sample by number of observation per firm

Annual obs	4	5	6	7	8	9	10	11	12	13
companies	26	30	29	15	21	24	11	18	52	42

Table A.3: Structure of sample by number of firms per year

year	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
firms	141	184	200	220	223	223	213	201	192	176	170	160	92

Table A.4: Total shareholdings by category of owner

		(1)	(2)	(3)	(4)	(5)	(6)
		all		small firms		large firms	
		Identified equity	% of id. equity	Identified equity	% of id. equity	Identified equity	% of id. equity
1	Total financial institutions	39.85	63.07	33.50	47.48	45.29	76.42
		(19.60)	*(29.30)*	*(19.88)*	*(26.39)*	*(17.63)*	*(24.72)*
2	pension funds	9.56	15.54	6.86	9.62	11.86	20.62
		(7.29)	*(12.19)*	*(6.39)*	*(8.98)*	*(7.24)*	*(12.30)*
3	Insurance companies	10.55	17.44	5.85	8.21	14.57	25.34
		(8.72)	*(14.86)*	*(6.52)*	*(8.99)*	*(8.35)*	*(14.33)*
4	Other financial institutions	19.74	30.09	20.78	29.64	18.85	30.47
		(13.57)	*(18.25)*	*(15.16)*	*(20.51)*	*(11.98)*	*(16.07)*
5	individuals	20.94	28.49	32.36	43.48	11.15	15.65
		(23.04)	*(29.03)*	*(22.94)*	*(27.70)*	*(18.11)*	*(23.46)*
6	Company	3.91	5.64	5.10	7.24	2.88	4.28
		(9.01)	*(12.34)*	*(9.50)*	*(13.06)*	*(8.45)*	*(11.51)*
7	Sepon	0.70	1.25	0.63	1.08	0.75	1.39
		(1.13)	*(2.36)*	*(1.13)*	*(2.40)*	*(1.13)*	*(2.31)*
8	Other non financial institutions	0.93	1.55	0.52	0.72	1.29	2.26
		(1.77)	*(2.75)*	*(1.60)*	*(2.08)*	*(1.83)*	*(3.04)*
9	Total identified	66.32	100	72.12	100	61.36	100
		(17.20)		*(16.28)*		*(16.40)*	

Notes: Reported statistics are unweighted averages and in italics in parentheses unweighted standard deviations calculated on the unbalanced panel of 268 firms and 2,395 observations over the 1985-1997 period. Small (large) firms have in the year they enter the sample a number of employees lower (higher) than the median firm in that particular year. Row 1 reports summary statistics for the proportion of equity held by financial institutions. Rows 2 to 4 report descriptive statistics for each of the financial institutions included in this category: row 2 refers to pension funds, row 3 to insurance companies and row 4 to other financial institutions. Row 5 reports summary statistics for individual owners. Rows 6 to 8 refer to the other categories of identified ownership : row 6 to company, i.e. to non-financial companies, row 7 to Sepon Ltd, the Stock Exchange Clearing company, i.e. it includes equity that is in the process of being sold at the time of measurement, and row 7 to 'other institutions', i.e. non-financial institutions, e.g. universities, local government bodies etc. The last row reports the proportion of equity for which the CDA Spectrum databases identifies the ultimate owner. See also section 2.3 for details on the data and variables definitions.

Table A.5: Distribution of ownership concentration measures in the sample

	Sample	p10	p25	p50	p75	p90
top5	whole	14.09	21.46	32.77	49.23	67.13
	small	24.29	30.14	40.76	57.71	69.69
	large	11.60	15.91	22.10	33.54	53.60
top5inst	whole	0.00	14.38	40.33	81.00	100.00
	small	0.00	5.60	28.48	59.70	85.54
	large	9.83	26.11	64.08	100.00	100.00
top5ind	whole	0.00	0.00	14.88	68.85	94.46
	small	0.00	9.84	40.28	80.76	100.00
	large	0.00	0.00	0.00	18.46	74.46
block5	whole	0.00	9.50	25.57	47.51	67.02
	small	10.86	22.29	37.89	57.09	67.51
	large	0.00	0.00	11.46	24.96	52.22
block5inst	whole	0.00	0.00	5.61	12.34	21.16
	small	0.00	0.00	6.62	15.63	25.01
	large	0.00	0.00	0.00	7.86	16.04
block5ind	whole	0.00	0.00	5.08	27.75	49.23
	small	0.00	0.00	13.06	39.35	61.78
	large	0.00	0.00	0.00	5.28	31.34

Notes: The table refers to the sample of 2,395 observations. The variables reported as defined as follows: TOP5, the cumulative percentage of all shares held by the largest five shareholders; TOP5INST the proportion of shares held by the five largest shareholders owned by institutions; TOP5IND, the proportion of shares held by the five largest shareholders owned by individuals; BLOCK5, the cumulative percentage of all shares held in blocks greater or equal to 5%; BLOCK5INST, the proportion of shares held in blocks greater or equal to 5% by institutions; BLOCK5IND, the proportion of shares held in blocks greater or equal to 5% by and by individuals.

Table A.6: AR1 test: t-test using OLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Var $_t$	$ln(VA)$	$ln(SALES)$	$ln(K)$	$ln(EMP)$	top5	top10	block5
Dep Var $_{t-1}$	0.994	0.995	0.995	0.990	0.937	0.944	0.935
	(0.002)	*(0.002)*	*(0.002)*	*(0.003)*	*(0.011)*	*(0.008)*	*(0.009)*
F(1,267)	6.85	6.65	5.23	11.07	36.40	48.34	50.71
p-value	0.009	0.010	0.023	0.001	0.000	0.000	0.000
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	$ln(\frac{VA}{EMP})$	$ln(\frac{SALES}{EMP})$	$ln(\frac{K}{N})$	top5inst	top5ind	block5inst	block5ind
Dep Var $_{t-1}$	0.957	0.970	0.959	0.879	0.936	0.880	0.922
	(0.011)	*(0.007)*	*(0.007)*	*(0.009)*	*(0.008)*	*(0.014)*	*(0.013)*
F(1,267)	15.51	19.67	36.77	171.91	64.41	72.98	36.16
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The coefficients (robust standard errors in parenthesis and italics) are estimated by Least Squares on an unbalanced panel of 268 observations and 2,395 firms.

Table A.7: Ownership pattern during the 1985-1997 period

		1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
(1)	Top1	13.26	14.29	13.34	14.18	14.52	14.27	14.83	14.44	13.61	12.70	13.07	11.80	11.38
		(12.08)	*(12.97)*	*(11.32)*	*(13.09)*	*(12.93)*	*(12.53)*	*(12.88)*	*(13.36)*	*(11.92)*	*(10.46)*	*(12.12)*	*(9.83)*	*(7.53)*
(2)	Top5	32.49	35.51	34.12	35.18	36.07	36.07	37.11	35.91	34.80	32.96	33.90	32.36	31.54
		(17.93)	*(18.39)*	*(17.52)*	*(18.76)*	*(18.19)*	*(17.94)*	*(18.30)*	*(18.11)*	*(17.11)*	*(15.98)*	*(16.78)*	*(15.53)*	*(14.33)*
(3)	Top10	43.20	47.74	46.06	47.13	48.31	48.40	49.93	48.80	47.64	45.61	46.33	44.90	44.08
		(19.58)	*(19.75)*	*(19.10)*	*(20.08)*	*(19.32)*	*(19.20)*	*(19.49)*	*(19.33)*	*(18.88)*	*(18.09)*	*(18.37)*	*(17.41)*	*(16.41)*
(4)	Herfindahl Index	0.05	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.04
		(0.08)	*(0.09)*	*(0.07)*	*(0.10)*	*(0.09)*	*(0.09)*	*(0.09)*	*(0.09)*	*(0.08)*	*(0.06)*	*(0.08)*	*(0.07)*	*(0.03)*
(5)	% held in blocks larger than 5%	24.53	27.69	25.84	27.11	27.98	28.71	30.14	28.49	27.70	25.22	26.17	24.13	23.00
		(21.65)	*(22.99)*	*(21.81)*	*(23.14)*	*(22.28)*	*(21.95)*	*(22.47)*	*(22.04)*	*(20.99)*	*(19.84)*	*(20.73)*	*(20.41)*	*(19.74)*
(6)	% of top5 owned by individuals	30.80	30.60	29.92	29.75	29.65	27.82	26.63	23.76	24.36	23.32	21.78	18.47	17.69
		(35.77)	*(35.67)*	*(35.00)*	*(35.50)*	*(35.98)*	*(33.74)*	*(32.72)*	*(31.14)*	*(32.10)*	*(31.49)*	*(30.35)*	*(29.07)*	*(28.31)*
(7)	% of top5 owned by institutions	51.33	49.09	49.26	48.91	49.37	49.79	52.49	53.44	53.48	55.06	51.39	45.65	46.11
		(35.12)	*(34.58)*	*(34.57)*	*(34.76)*	*(35.05)*	*(34.96)*	*(34.43)*	*(34.85)*	*(33.51)*	*(32.95)*	*(29.90)*	*(28.05)*	*(25.72)*
(8)	% of top10 owned by individuals	30.66	29.60	29.36	28.47	28.07	26.31	25.22	22.64	23.17	21.98	20.13	17.65	16.40
		(32.59)	*(32.76)*	*(32.12)*	*(31.94)*	*(31.96)*	*(29.98)*	*(29.07)*	*(27.67)*	*(28.34)*	*(27.84)*	*(26.51)*	*(25.63)*	*(24.79)*
(9)	% of top10 owned by institutions	52.27	50.45	50.40	50.46	51.44	52.48	54.51	55.11	56.35	57.83	54.41	49.14	51.22
		(31.13)	*(31.75)*	*(30.89)*	*(30.99)*	*(30.73)*	*(30.58)*	*(30.03)*	*(30.23)*	*(29.61)*	*(28.81)*	*(25.61)*	*(22.68)*	*(21.70)*
(10)	% of equity held by largest individual	6.63	7.10	6.88	7.05	7.36	7.11	7.14	6.82	6.86	6.57	6.31	5.20	4.82
		(8.17)	*(8.09)*	*(7.77)*	*(8.34)*	*(8.85)*	*(8.57)*	*(9.10)*	*(9.19)*	*(9.17)*	*(9.16)*	*(9.06)*	*(7.39)*	*(6.90)*
(11)	% held by institutions in blocks larger than 5%	7.36	7.81	7.24	7.81	8.92	9.78	11.12	10.38	10.75	10.44	10.58	8.96	8.96
		(10.64)	*(10.89)*	*(10.14)*	*(10.64)*	*(11.97)*	*(12.56)*	*(12.97)*	*(11.87)*	*(12.29)*	*(12.07)*	*(11.87)*	*(10.74)*	*(10.52)*
(12)	% held by individuals in blocks larger than 5%	11.76	12.88	12.26	12.38	12.51	11.62	11.22	10.26	10.60	9.73	9.17	7.65	6.61
		(18.84)	*(19.51)*	*(18.81)*	*(19.43)*	*(19.10)*	*(18.02)*	*(17.85)*	*(17.07)*	*(17.08)*	*(16.63)*	*(16.16)*	*(15.10)*	*(13.57)*

Notes: The figures reported are unweighted averages (standard deviations in italics and parentheses) for each year. The sample is an unbalanced panel of 268 firms over the 1985-1997 with 2,395 observations.

Appendix B

Appendix to Chapter 3

B.1 Variable Definitions

- Capital stock: capital stock was calculated using a perpetual inventory method (PIM). For a more detailed description of the method adopted we refer to Martin (2002)
- Deflators: to deflate output measures (gross output and value added) we use producer price indices at the 4-digit SIC92 industry level. To deflate intermediates, we use material price deflators at the 2-digit SIC92 industry level. The base year is 1995. Capital stock is deflated using investment deflators with base year 1995; for years pre-1995 these are implicitly derived from nominal and real sectoral ONS historical investment series. From 1995 onwards I use the publicly available MM17 series.
- Foreign plants are plants owned by foreign owned enterprise groups.
- Country groups:

EUnorth includes plants owned by Austria, Belgium, Denmark, Finland , Luxembourg, Sweden and Republic of Ireland.

EUsouth includes plants owned by Italy, Spain and Canary Islands, Portugal and Greece.

Tax includes plants owned by British Virgin Islands, Channel Islands, Isle of Man, Liechtenstein, Antigua and Barbuda, Cyprus and US Virgin Islands.

otherEurope includes plants owned by Norway and Switzerland.

otherOECD includes plants owned by Australia, Canada, Czech Republic, Iceland, Mexico, Poland, South Korea and Turkey.

other is a residual category that includes plants owned by the rest of the world and plants which are foreign owned but whose nationality is unknown.

- Weights are calculated using the register employment information on the basis of 4 digit sector, region and employment cells. For each cell i the weight is calculated as $\frac{\text{Number of plants in register in cell i}}{\text{Number of selected plants cell i}}$.

B.2 The monotone relationship between profits and shocks

Start by noting that given our assumption of a homogenous production function (equation 3.7) we can write the cost minimization problem as:

$$\breve{C}(\breve{K}_{it}, \mathbf{w}_{Vit}) = \min_{\breve{\mathbf{X}}_{Vit}} \sum_{z \neq K} w_{zit} \breve{X}_{zit} \text{ s.t. } 1 = f\left(\breve{K}_{it}, \breve{\mathbf{X}}_{Vit}\right) \tag{B.1}$$

where w_{zit} represents the cost of factor z and $\breve{K}_{it} = \frac{K_{it}}{\breve{Q}_{it}}$ with $\breve{Q}_{it} = \left(\frac{Q_{it}}{A_{it}}\right)^{\frac{1}{\gamma}}$. $\breve{\mathbf{X}}_{Vit}$ collects the same transformation for all variable production factors in a vector. Total cost become in terms of Equation B.1

$$C_{it} = \breve{C}_{it} \breve{Q}_{it} \tag{B.2}$$

Next consider the profit function.

$$\Pi_{it}(K_{it}, \lambda_{it}, a_{it}, \mathbf{w}_{it}) = R_{it} - C_{it}$$

Given the demand function 3.4 and the cost function B.2 we can write it as

$$\Pi_{it}(K_{it}, \lambda_{it}, a_{it}, \mathbf{w}_{it}) = \left(\frac{\Lambda_{it} R_t}{P_t}\right)^{\frac{1}{\eta}} P_t Q^{1-\frac{1}{\eta}} - \breve{C}_{it} \breve{Q}_{it} \tag{B.3}$$

Note that the firm's profit maximization first order condition is

$$\left(1-\frac{1}{\eta}\right)\frac{R_{it}}{Q_{it}}=\frac{1}{\gamma}z(\breve{Q}_{it},\breve{K}_{it})\frac{\breve{Q}_{it}}{Q_{it}} \tag{B.4}$$

where

$$z(\breve{Q}_{it},\breve{K}_{it})=\frac{\partial\breve{C}_{it}}{\partial\breve{Q}_{it}}\breve{Q}_{it}+\breve{C}_{it} \tag{B.5}$$

Finally, note that the derivatives of profit with respect to changes in λ_{it} and a_{it} are

$$\frac{\partial\Pi_{it}}{\partial\lambda_{it}}=\mu^{-1}R_{it}$$

and

$$\frac{\partial\Pi_{it}}{\partial a_{it}}=z(\breve{Q}_{it},\breve{K}_{it})\frac{1}{\gamma}\left(\frac{Q_{it}}{A_it}\right)^{\frac{1}{\gamma}}=\mu^{-1}R_{it} \tag{B.6}$$

where the last equality follows from the first order condition B.4[1] and

$$\mu=\left(1-\frac{1}{\eta}\right)^{-1}$$

As a consequence of all these results we get for the total differential of profits

$$d\Pi_{it}=R_{it}\frac{1}{\mu}\left(d\lambda_{it}+da_{it}\right)=R_{it}d\omega_{it} \tag{B.7}$$

which establishes that there is a positive relationship between profits and composite shock index ω_{it}.

B.3 Testing if μ is constant

In this section, we describe a simple test of the hypothesis that μ is uniform across each 4 digit sector based on over-identifying restrictions. As expected, the null hypothesis is rejected in the majority of sectors. Column 3 of table 6.4 shows estimates of equation 3.20 on a restricted sample of plants in sectors where the null hypothesis of uniform μ cannot be rejected to check the robustness of our results. Our test works as follows: if we want to allow for a more general market structure then the coefficient of capital in Equation 3.18 is not constant but depends on the

[1]This is an application of the envelope theorem

exogenous quality parameter of the firm, λ_{it}.[2]

$$r_{it} - vi_{it} = \beta^K_{it-1} k_{it} + g(k_{it-1}, \Pi_{it-1}) + \nu_{it} \tag{B.8}$$

where $\beta^K_{it-1} = \frac{\gamma}{\mu}(\lambda_{it-1})$. [3] If we nevertheless used a specification with constant β^K we are faced with the following situation:

$$r_{it} - vi_{it} = \beta^K k_{it} + g(k_{it-1}, \Pi_{it-1}) + \nu_{it} + (\beta^K_{it} - \beta^K) k_{it} \tag{B.9}$$

where β^K represents the constant capital coefficient we are trying to estimate. Equation B.9 shows that there is unaccounted for heterogeneity which is correlated with the explanatory variables, thus an estimator based on zero correlation conditions between k_{it}, Π_{it-1}, etc. and the error term breaks down. Equation B.9 is the alternative specification to the hypothesis we want to test, namely that β_K is constant. Thus it can help us find restrictions which allow us to test our hypothesis. The first set of these restrictions we mentioned already: zero correlation between $\breve{\varepsilon}_{it} = r_{it} - vi_{it} - \beta^K k_{it} - g(k_{it-1}, \Pi_{it-1})$ and the explanatory variables in B.9:

$$E\{\breve{\varepsilon}_{it} X_{it}\} = 0 \tag{B.10}$$

where $X_{it} \in \{k_{it}, k_{it-1}, \Pi_{it-1}\}$. An additional instrument would be the interaction between current capital stocks and last periods demand shock, $k_{it} \cdot \lambda_{it-1}$. The problem with this is of course that λ_{it-1} is not observed. Note however that since λ_{it} is a component of ω_{it} and although ω_{it} is not observed we have a way of controlling for it: we approximate it by a polynomial in Π_{it} and k_{it}. This implies that we can derive additional zero correlation conditions for the interaction of k_{it} with all lagged polynomial terms, thus under the null $\breve{\varepsilon}_{it}$ will not be correlated with terms such as $k_{it} \cdot k_{it-1} \cdot \Pi_{it-1}$, etc. Note here, that it is crucial to make the assumption about sluggish prices. Because there would always be a correlation between ν_{it} and ω_{it} we could not make a similar argument starting from a zero correlation condition between $k_{it} \cdot \lambda_{it}$ and $\breve{\varepsilon}_{it}$. Finally note that, because of the presence of k_{it} in $\breve{\varepsilon}_{it}$, under

[2]For simplicity I make the formal argument in terms of log levels and not deviations from log values of the median plant as in section 3.5.3. The argument can be made similarly in both cases.

[3]Note that in order to use our test I implicitly need to assume that there is a certain sluggishness in price setting: markups depend on last period's realization of the λ-shock, as I describe below.

Table B.1: Statistics on double fixed effects groups

	(1) obs	(2) plants	(3) firm
min	2	1	1
max	634	201	55
median	3	1	1
groups	6754		
obs	28338		

Notes: The first panel reports summary statistics for the double fixed effects groups (DFG) in our sample. Column 1 row 1 shows that the smallest DFG consists of 2 observations, the largest of 634 and the median group of 3 observations. Columns 3 and 4 report the same statistics for the numbers of plants and firms.

the alternative hypothesis (B.9), all these zero correlation conditions break down and they are thus indeed a means to test our hypothesis.
We implement the test as a Sargan-Test where we use the restrictions in $B.10$ to exactly identify all required parameters and then test the zero correlation of the restrictions from the polynomial interactions as a χ^2-distributed statistic.

B.4 A double fixed effects approach

We suggested that Equation 3.22 could also be estimated using a double fixed effects methodology. This section discusses how this could be done and the problems it raises.

Firm and plant effects can be identified separately to the extent that plants move between firms. Abowd et al. (2002b) have laid out in detail which firm and plant effects we can hope to identify:[4] They define sets of 'double fixed effect groups' (DFG). A DF group DFG_g is defined as the set of all firms and plants which interact over the sample period. A firm and a plant interact simply if the plant is owned by the firm. Two plants interact if they are both owned by the same firm at some but not necessarily the same point in time. Two firms interact if they own the same plant at different points in time.

Abowd et al. show that for each plant and each firm in a DFG one can identify a fixed effect which is informative about its productivity relative to the group average,

[4] Abowd et al. work with matched employer-employee panels but their results apply to our problem immediately once plants take on the role of employees and firms the role of employers.

Table B.2: Double fixed effects regression results

	(1)	(2)
US	-0.031	0.039
	(0.013)**	(0.024)*
MNE	0.002	0.020
	(0.018)	(0.018)
FOR	0.026	0.028
	(0.018)	(0.025)
green GB non MNE		0.000
		(0.021)
green US		0.030
		(0.054)
green FOR		0.037
		(0.063)
green MNE		-0.001
		(0.037)
obs	2842	2865

Notes: Bootstrapped standard errors in parentheses. Coefficients and standard errors are from the third-stage of the double-fixed effects model. In column 1 the dependent variable is firm fixed effects estimated in the second-stage. **ever US firm** is 1 for all US firms. **ever MNE firm** is 1 for all MNE firms. **ever FOR firm** is 1 for non US foreign firms. In Column 2 the dependent variable is the plant fixed effects estimated in the second-stage **ever MNE plant** is 1 for all plants that have ever been owned by a MNE over the course of the sample period. Similarly for the ever US and ever other foreign dummies. The **green** dummies take value one for all plants that are established during the course of the sample period (1996-2000), **green GB non MNE** is one for plants owned by domestic firms when established. **green MNE** is one for plants owned by MNE firms when established. **green US (green FOR)** is one for plants owned by US (other foreign) firms when established.
* significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level.
*** significantly different from zero at the 1 percent level.

where the group average includes the fixed effect of an omitted reference firm, μ_R, and an omitted reference plant α_r. Thus, any estimated fixed effect has to be interpreted as relative to the omitted plant and firm.

Table B.1 reports some statistics on these groups. Consider first the second panel which reports that there are in total 6754 such groups in our dataset. Also note that the number of observations has now reduced because we can only use observations from plants we observe at least twice. Panel 1 reports various statistics on these 6,754 groups. We see that the majority of groups is rather small. Both the median number of plants and firms (row 3 in columns 2 and 3) is 1 one which means that our dataset consists mainly of firms that own one plant which is never sold. For these there is no chance of separating firm and plant effects. Our sample thus reduces to those groups which consist of at least 2 plants or firms. This corresponds to about one third of our original sample.

After establishing how many fixed effects can effectively be identified the double fixed effects problem is in principle nothing else but a regression on dummies for each plant and firm whose fixed effect can be identified. However, this runs into computational problems because of the sheer size of the matrices that are to be inverted. Abowd et al. apply some advanced linear algebra techniques to get round this problem. However, since all coefficients' estimates are relative to a group, neither efficiency of consistency is lost if estimates are obtained separately for each group. In our case the largest group consists of 55 firms and 201 plants. This is still in the range feasible for a normal dummy variable regression, which is our strategy. In each group we can then estimate the fixed effects of each plant and firm except for one reference plant and firm:

$$\alpha_i - \widehat{\alpha_r} - \mu_R \quad \text{and} \quad \mu_J - \widehat{\alpha_r} - \mu_R$$

where α_r is the reference plant and μ_R the reference firm.
To examine the existence of MNE firm and plant effects as discussed in Section 3.6 we regress these estimated fixed effects on MNE plant and firm dummies; i.e. for the firm effect:

$$\mu_J - \widehat{\alpha_r} - \mu_R = \beta_{MNE^{ever}_{Firm}} MNE^{ever}_{J(i,t)} + \varepsilon_{it} \tag{B.11}$$

Can we hope that $\beta_{MNE^{ever}_{Firm}}$ provides a consistent estimator of

$$E\{\mu_J | MNE^{ever}_{J(i,t)} = 1\} \tag{B.12}$$

Only if we can assume that there is no systematic correlation between $\mu_J + \alpha_i$ and $MNE^{ever}_{J(i,t)}$. However, this is unlikely because multinational firms are more likely to interact with other multinational firms or with domestic firms which have higher productivity so that $E\{\mu_J|1\} > E\{\mu_J|0\}$. This would introduce a downward bias in our estimate of $\beta_{MNE^{ever}_{Firm}}$. A similar argument applies to our estimate of the MNE plant effect. Given the downward bias we expect that regressions of B.11 and the equivalent plant equation lead to lower MNE firm and MNE plant estimates than the results found in Section 3.6.

Table B.2 shows estimates of equation B.11 in column 1 and the equivalent plant level equation in Column 2. All point estimates are lower than the comparable estimates in Section 3.6 and most effects are found to be non significant. Only the US plant effect is still significant at the 10 percent level (column 2, row 1), whereas The US firm effect estimate is now negative and significant at the 5 percent level.

Appendix C

Appendix to Chapter 4

C.1 The Community Innovation Survey

C.1.1 Cleaning the Community Innovation Survey

Some variables in the original CIS3 data are missing. When possible we have tried to fill in these gaps in the data in several ways, using, when available, information from the CIS3 survey.

- Exports: we have replaced missing with zero wherever the firm had answered that the enterprise's largest market was local, regional or national.
- Largest market: if the firm has positive exports or declared we replace missing answers to the largest market with "international".

We decided to drop all observations for which any of the following information remained missing :

- All the indicators on innovative activity
- Innovative sales when the enterprise declares to be a product innovator

For the regression analysis we also dropped observations for which any of the following information is missing:

- Proportion of graduate employees
- Enterprise's exporting activity

Table C.1: Details of CIS2 and CIS3 samples

		(1) CIS 2	(2) CIS3
1	Number of sampled reporting units	5,892	19,602
2	Number of responding Reporting Units	2,339	8,172
3	Number of sampled reporting units in service sector	1,986	8,622
4	Number of responding Reporting Units in service sector	743	3,605
5	Number of sampled Reporting Units in Production	3,906	10,980
6	Number of responding Reporting Units in Production	1,596	4,567
7	Number of Reporting Units in Manufacturing excluding sector 23 and Northern Ireland	1,405	3,347

Notes: Production includes manufacturing; mining; electricity, gas and water; construction. Services include distribution and services: wholesale trade except of motor vehicles; transport, storage and communication; financial intermediation and real estate, renting and business activities. Sector 23 is defined as "manufacturing of coke, refined petroleum products and nuclear fuel".

- Estimated turnover due to new or improved products missing but firm declares to have product innovated.
- observations that had missing or no innovative expenditure but had positive innovation outcomes.

C.1.2 The Community Innovation Survey Samples

Table C.1 sets out the details the composition of the innovation surveys: from CIS2 we have usable data on 2,339 respondents (Row 2, column 1) of which 1,596 in production (Row 6 column 1) and 743 in services (Row 4, column 1). For CIS3 the number of respondents is 8,172 (Row 2, column 2), of which 3,605 in the service sector (Row 4, column 2) and 4,567 in the production sectors (Row 6, column 2).

C.1.3 Survey Questions in CIS3

- MEASURES OF KNOWLEDGE OUTPUTS (ΔK_i)

  Process Innovation During the three year period 1998-2000, did your enterprise introduce any technologically new or improved processes for producing or supplying products which were new to your firm?

  Product Innovation During the three year period 1998-2000, did your enterprise introduce any technologically new or significantly improved products (goods or services) which were new to your firm?

% Turnover due to new and improved products Please estimate how your turnover in 2000 was distributed between products (goods or services) introduced during the period 1998-2000 which were: New to your firm + Significantly improved (%).

Patent Protection During the period 1998-2000, please indicate the importance to your enterprise of the following methods to protect innovations?

Number of Patents How many patents, if any, did your enterprise apply for during the period 1998 to 2000?

- **MEASURES OF KNOWLEDGE INPUTS** (H_i)

R&D Personnel How many persons were involved in R&D activities within your enterprise in 2000 (in full time equivalents)?

Proportion Scientists and Engineers Approximate proportion [of employees] educated to degree level or above [in the fields of] science and engineering subjects

Intramural R&D Please tick if expenditure in the category [of] Intramural research and experimental development (R&D); [and if so ticked], please estimate innovative expenditure in 2000, including personnel and related investment expenditures (no depreciation)

- **MEASURES OF KNOWLEDGE FLOWS** (K'). Sources of Information for Innovation Activities: "Please indicate the sources of knowledge or information used in your technological innovation activities, and their importance during the period 1998-2000."

We adopt two alternative method to construct variables that describe the information flow to the firm. The groups considered are reported below.[1] The first method summarises information from the CIS according to the following criterion: the information flow variables take the maximum values between those reported in that particular group, normalized to one. This is our preferred method. The second method follows Cassiman and Veugelers (2002)

[1]Note that given minor differences between the two waves of the surveys we have to slightly modify the definitions of our variables accordingly.

and summarises information from the CIS according to the following criterion: the information flow variables take the average values between those reported in that particular group, normalized to one.

Internal Information from Self Within the enterprise

Internal Information from Group Other enterprises within the enterprise group

Vertical Information from Suppliers and Customers Suppliers of equipment, materials, components or software + Clients or customers

Information from Competitors Competitors

Commercial Information Consultants + Commercial laboratories / R&D enterprises

Free Information Professional conferences, meetings + Trade associations + Technical/trade press, computer databases + Fairs, exhibitions

Regulatory Information Technical standards + Environmental standards and regulations + Health and safety standards and regulations

Information from Universities Universities or other higher education institutes + Private research institutes Information from Government Government research organisations + Other public sector (e.g., Government Offices)

Note that the question in CIS2 reads as follows: "How important to your enterprise are the following as sources of information for new technological innovation projects or for the completion of existing projects?" The information sources that have a slight different definitions in CIS2 are the following:

Information from Competitors Competitors + patent disclosures

Commercial information Consultancy enterprises

Information from universities Universities or other higher education institutes+ Private non profit research institutes +Research associations or other independent Research and technology organisations

Table C.2: CIS 2 and CIS3 panel

		(1) CIS 2	(2) CIS3
1	Number of Reporting Units	2,339	8,172
2	Number of Reporting Units in Manufacturing (exc. SIC 23 and NI)	1,453	3, 425
3	Number of reporting units in both surveys	787	
4	Number of reporting units in manufacturing in CIS2 and in CIS3 (exc. sector 23 and NI)	509	

Notes: Sector 23 is defined as "manufacturing of coke, refined petroleum products and nuclear fuel". NI: Northern Ireland.

information from Government Government institutes+ Training and enterprise councils+Business links

- **OTHER CONTROL VARIABLES**

Employment Number of employees [at the enterprise] (full time equivalents)

Structural Change Did any of the following significant changes occur to your enterprise during the three year period 1998-2000?

- *Established*: The enterprise was established
- *Merger*: Turnover increased by at least 10% due to merger with another enterprise or part of it.
- *Sale or Closure*: Turnover decreased by at least 10% due to sale or closure of part of the enterprise.

C.1.4 Constructing an innovation panel

One of our aims is to construct an innovation panel, using information from CIS2 and CIS3. The results of this exercise are reported in Table C.1.4

787 enterprises are in both surveys. Some of them are recorded in the manufacturing sector in CIS2 and in the service sector in CIS3. Since in CIS3 the survey is the same for both sector we decided to consider these enterprises as being part of the manufacturing sector if they are in the manufacturing sector according to the ARD. What information can we get from the panel? Although the gist of questionnaire for CIS2 and CIS3 is the same, the two questionnaires differ in several respects, so that the construction of an innovation panel needs some caution. Firstly the main questions and definitions of both product and process innovation differ. In particular, the wording of the question on process innovation might lead to some

ambiguity: some firms might tend to report process innovations only if these were used for producing products which were new to the firm. Secondly, the CIS3 questionnaire is the same for both production and service sector while CIS2 had two different questionnaires for services and production. Thirdly, in CIS2 an additional problem arises because companies can skip a part of the questionnaire by declaring that they have not engaged in any innovative activity and do not have any intention to start innovative projects in the next five years while there are no filter questions in CIS3. Fourth, the ordering and the general layout/editing of the questions in the survey differs. This matters if we believe that respondents get tired of answering the questionnaire and become less attentive towards the end of the questionnaire.[2]

[2]Other differences concern the question regarding public support for innovation in CIS3 distinguishes between the source of the support (regional, central or European government), whereas in CIS2 the question entails a yes/no answer on whether the enterprise has received any central government financial support. Also, the classification of innovation-related public programs slightly differs among the two surveys. Lastly, there are differences in the lists of sources of information, in particular in CIS2 firms were asked whether patent disclosures constituted a valuable source of information for innovations, this questions has been excluded; whereas the questions on methods of innovation protection were added only in CIS3.

Appendix D

Appendix to Chapter 5

D.1 Data Cleaning

D.1.1 Cleaning the ARD

This section provides detail on how we cleaned the dataset and provide definitions for relevant variables. We cleaned the dataset according to the following criteria (partly following Hall and Mairesse (1995)).

First, we have removed all observations for which growth of value added, employment, capital and material inputs is missing.

Second, we drop any observation for which the average annual growth rate in value added, gross output or material inputs was more than 300 percent or less than -90 percent.

Third, we adopt a similar criterion for observations for which the average annual growth in labour and in capital is more than 200% or less than -50 percent.

D.1.2 Cleaning the Community Innovation Survey

Table C.1 in the Appendix to the previous chapter sets out the details the composition of the Community Innovation surveys. The analysis in this chapter use the third Community Innovation Survey (CIS3) and only includes the manufacturing sectors, except for the manufacturing of coke, refined petroleum products and nuclear fuel (Sector 23 of the 2-digit ISIC92 classification) because of the lack of deflators for the productivity measures in this sector. This leaves us with a sample of 3,425 reporting units in CIS3 (Row 4, column 2 of Table C.1). I also exclude businesses located in Northern Ireland, since ARD data for Northern Ireland was not made available. This leaves 3,347 in CIS3 (Row 8).

D.2 Variables definition

Many of the variables used in this chapter have been defined in Chapter 4. Below, I define the remaining variables.

Organisational innovation Did your enterprise make major changes in the following areas of business structure and Practices during the period 1998-2000 and how far did business performance improve as a result? Implementation of: new or significantly changed Corporate strategies or advanced management techniques or Organisational structures.

Innovation expenditures/activity Did your enterprise engage in the following innovation activities in 2000? Please estimate innovative expenditure in 2000, including Personnel and related investment expenditures (no depreciation). Total Innovation expenditure is defined as follows: as reported, if the total figure is not missing or calculated as the sum of reported Intramural R&D + Acquisition of external R&D + Acquisition of machinery and equipment + Acquisition of other external knowledge + All design functions + Internal or external training + Internal or external marketing.

Process Innovation During the three year period 1998-2000, did your enterprise introduce any technologically new or improved processes for producing or supplying products which were new to your firm?

Novel Process Innovation During the three year period 1998-2000, did your enterprise introduce any new or significantly Improved processes for producing or supplying products (goods or services) which were new to your industry?

Product innovation During the three year period 1998-2000, did your enterprise introduce any technologically new or significantly improved products (goods or services) which were new to your firm?

% turnover due to new and improved products Please estimate how your turnover in 2000 was distributed between products (goods or services) Introduced during the period 1998-2000 which were: New to your firm + Significantly improved (%)

Novel Product Innovation During the three year period 1998-2000, did your enterprise introduce any new or significantly Improved products (goods or services) which were also new to your enterprise's market?

% turnover due to novel product innovation Please estimate the share of turnover of these (novel) products in 2000

Public support for innovation Did your enterprise receive any public support (financial or other assistance and advice) for innovation-related activities in the period 1998-2000?

Financial support What were the sources of this public support for innovation-related activities in the period 1998-2000? Financial Support from Local or regional government, Central government (including institutions working on behalf of central Government) or The European Union

Non financial support Other Support from Local or regional government, Central government (including institutions working on behalf of central Government) or The European Union

Export Dummy Is your enterprise's largest market? International or Either Exports of goods in 1996 or 1998 positive.

Protection methods During the period 1998-2000, please indicate the importance to your enterprise of the following Methods to protect innovations?

Strategic Protection Complexity of design+ Lead-time advantage on competitors+ Secrecy

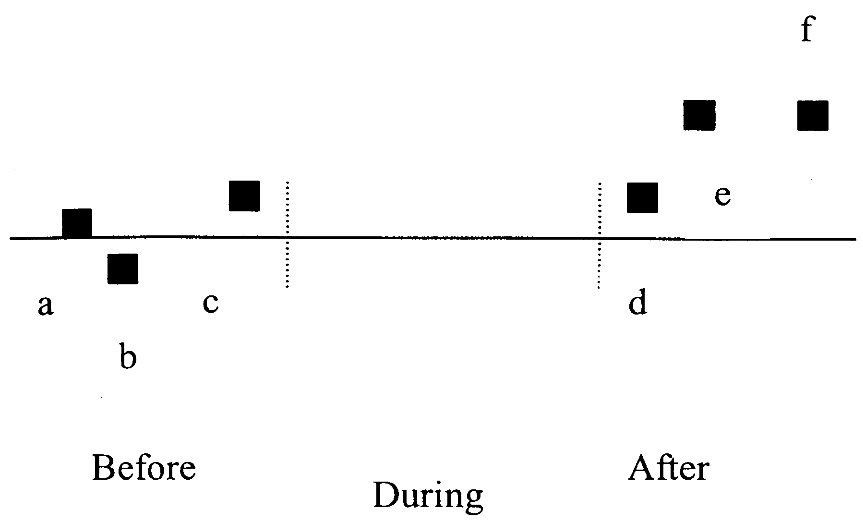
Formal (legal) Protection Registration of design+ Trademarks+ Patents+ Confidentiality agreements+ Copyright

Cooperation Did your enterprise have any co-operation arrangements on innovation activities with other Enterprises or institutions in 1998-2000?

D.3 TFP growth calculations

When calculating TFP growth, one incurs into issues related to the ARD being an unbalanced panel. To understand this issue consider figure D.1:

Figure D.1: Calculating TFP growth



There are three main issues: timing, measurement and the treatment of missing observations.

First, timing. Suppose there is no mismeasurement and no missing observations. If the innovation produces immediate effects on TFP then the appropriate measure would seem to be period d less period c. Against this, the effect might not be immediate, in which case one might want to look at periods e or f against period c, b or a. Equally, the question asks about an innovation at any time during 1998-2000, in which case one might want to compare period c with 'during' observations, or either of these and period d.

Second, TFP is likely to be mismeasured, in which case one would not like to rely on single observations but rather take an average, say averaging a, b and c, and d, e and f and measuring the difference between the averaged observations. In the diagram above for example, it might be that innovation does indeed raise productivity but periods c and d are subject to upward and downward measurement error respectively, in which case averaging would give a better picture. Note however, this might induce bias against finding any impact of the innovation if the effect on TFP is immediate and the averaging period is lengthy. Finally, with unbalanced panels due to sampling it is often the case that firms are not present for all three years, in which case one has to decide over which firms to average and how to annualise. We took the view that measurement problems means that averaging is desirable. Hence we did the following. Where all observations a to f were available, we averaged real outputs and real inputs a to c and d to f, then took logs and then calculated TFP growth, using

$$\Delta \ln TFP = \Delta\left(r_i - p_I\right) - \sum_{j=i}^{n} \bar{s}_j \Delta x_j$$

where the averaged shares are average a to c, plus average d to f, divided by 2. $\Delta \ln TFP$ is converted into an annual growth rate, in this example, by dividing by 3 (there being 3 years between observation d and c). We take logs, even though they do not necessarily measure growth rates, since theory indicates a relation between changes in log outputs and share weighted changes in log inputs.

Third, missing observations. Where not all observations of inputs and outputs are available, we calculate averages only for years where all inputs and outputs are present and convert $\Delta \ln TFP$ into an annual growth rate by dividing by the interval between the averaged observations after and before. If $\bar{s}_j$ is negative for a firm, we replace it by the average for the 4-digit industry, since we believe that output elasticities are better measured in this way rather than assuming firms with negative shocks, or measurement problems, have negative elasticities. Finally, we experimented, using these same methods, with changes in TFP calculated as changes between before and after, during and after and before and during.

There are two further issues, raised by the presence of missing observations. Assume that macro shocks shift TFP for all firms to low levels giving period b and high levels giving period e. Suppose there are two identical firms one of whom is observed in periods a and f, and one in period b and e. The macro shock introduces a spurious difference between them. To deal with this we entered time dummies for all periods over which firms are observed, thus removing the common element of TFP growth across all firms observed in a given year.

Formally, therefore, annualized TFP growth is calculated as follows:

$$\Delta \ln TFP = \frac{1}{\tau_T}\left[\Delta(r_i - p_I) - \sum_{j=i}^{n} \bar{\bar{s}}_j \Delta x_j\right] \text{ where:}$$

$$\Delta(r_i - p_I) = \frac{\sum_{t=t_2}^{T_2} (r_i - p_I)_t}{\tau_2} - \frac{\sum_{t=t_1}^{T_1} (r_i - p_I)_t}{\tau_1}; \Delta\bar{x} = \frac{\sum_{t=t_2}^{T_2} x_t}{\tau_2} - \frac{\sum_{t=t_1}^{T_1} x_t}{\tau_1}$$

and $\bar{\bar{s}}_j = \frac{\sum_t s_{it}}{(\tau_1 + \tau_2)}$

Small letters denote logarithms.τ_1 and τ_2 are the total number of years in which a firm is surveyed during the time periods before and after. is the total number of periods the firm is observed during the before and after periods.

D.4 Additional results

Table D.1: Estimates of the knowledge production: novel innovations

	(1)	(2)	(3)	(4)
dep. var	novel products		novel process	
ln(employment)	-0.0009	0.0010	0.0057	0.0059
	(0.0016)	(0.0020)	(0.0030)*	(0.0049)
ln(age)	-0.0031	-0.0006	0.0072	0.0098
	(0.0030)	(0.0036)	(0.0055)	(0.0088)
Age_{dummy}	-0.0009	-0.0016	-0.0162	-0.0215
	(0.0054)	(0.0061)	(0.0082)**	(0.0134)
Exporter	0.0150	0.0112	-0.0027	-0.0061
	(0.0050)***	(0.0059)*	(0.0088)	(0.0137)
group	-0.0089	-0.0096	-0.0118	-0.0196
	(0.0045)**	(0.0050)*	(0.0075)	(0.0115)*
mneUK	0.0230	0.0124	0.0378	0.0434
	(0.0075)***	(0.0084)	(0.0219)*	(0.0287)
foreign	0.0184	0.0097	0.0130	0.0291
	(0.0072)**	(0.0081)	(0.0160)	(0.0254)
non financial support	-0.0009	-0.0106	0.0268	0.0419
	(0.0074)	(0.0086)	(0.0198)	(0.0297)
cooperation	0.0164	0.0147	0.0466	0.0515
	(0.0044)***	(0.0050)***	(0.0143)***	(0.0189)***
Info from plant	0.0562	0.0538	0.0937	0.1257
	(0.0069)***	(0.0078)***	(0.0133)***	(0.0194)***
Info from group	0.0032	0.0034	0.0023	0.0061
	(0.0059)	(0.0068)	(0.0110)	(0.0163)
vertical Info	0.0231	0.0279	0.0256	0.0481
	(0.0077)***	(0.0088)***	(0.0143)*	(0.0216)**
Info from competitors	-0.0068	-0.0166	-0.0423	-0.0742
	(0.0071)	(0.0082)**	(0.0140)***	(0.0214)***
Commercial Info	-0.0034	-0.0031	0.0102	0.0174
	(0.0071)	(0.0080)	(0.0131)	(0.0199)
Free Info	0.0100	0.0038	0.0222	0.0183
	(0.0072)	(0.0084)	(0.0139)	(0.0215)
Info from regulation	0.0031	0.0123	-0.0006	0.0185
	(0.0065)	(0.0075)*	(0.0125)	(0.0189)
Info from universities	0.0101	0.0114	0.0052	0.0237
	(0.0080)	(0.0091)	(0.0145)	(0.0221)
Info from government	-0.0069	-0.0019	-0.0117	-0.0324
	(0.0085)	(0.0096)	(0.0158)	(0.0238)
Innovation expenditure/total sales	0.0711	0.0435	0.1512	-0.0477
	(0.0214)***	(0.0299)	(0.0349)***	(0.1006)
Observations	2598	1905	2555	1818

Notes: In columns 1 and 2 I report the conditional marginal effects of a tobit equation, with as dependent variable the proportion of sales accounted for by novel products (new the market). In columns 3 and 4 I report the marginal effects of a probit equation with dependent variable a binary variable that is one if the firm has introduced a process innovation which is new to the industry. In columns 1 and 3 I use the innovation expenditure variable as reported in the survey, in columns 2 and 4 I use innovation expenditure calculated from the estimates of equation 5.15. Regressors included in all columns but not reported in the table are: 3 indicators for structural change (startup, merger and closure), 10 regional dummies and 3-digit industry dummies.

Table D.2: Estimates of the R&D investment equation

	(1) level	(2) propensity	(3) level	(4) propensity
$ln(employment)$	0.2408	0.1109	0.2213	0.0411
	(0.1292)*	(0.0691)	(0.1348)	(0.0704)
$ln(MKT_{share_{i,t-1}})$	-0.3439	-0.0863	-0.3521	-0.0596
	(0.1081)***	(0.0596)	(0.1136)***	(0.0600)
$ln(age)$	-0.1153	0.0350	-0.0945	0.0269
	(0.1172)	(0.0682)	(0.1208)	(0.0710)
Age_{dummy}	0.0943	0.0470	0.0826	0.1095
	(0.1911)	(0.1160)	(0.1923)	(0.1206)
$Export_{dummy}$	-0.0010	0.3969	-0.0223	0.3098
	(0.2213)	(0.0999)***	(0.2223)	(0.1058)***
group	-0.2311	-0.0409	-0.2836	-0.0806
	(0.1486)	(0.0926)	(0.1467)*	(0.0956)
mneUK	0.0526	0.2979	0.0196	0.2619
	(0.2219)	(0.1291)**	(0.2181)	(0.1304)**
foreign	-0.0228	0.4453	-0.0646	0.4806
	(0.2062)	(0.1289)***	(0.2026)	(0.1314)***
financial support	0.6799		0.7318	
	(0.1849)***		(0.1876)***	
formal protection	0.3065	0.3280	0.1842	0.1076
	(0.2180)	(0.1275)**	(0.2118)	(0.1318)
strategic protection	0.4085	1.1466	0.1617	0.8375
	(0.2942)	(0.1299)***	(0.2547)	(0.1412)***
$\%scientists\&engineers$	2.1251	0.9062	1.8666	0.4803
	(0.5071)***	(0.3571)**	(0.5216)***	(0.3573)
$\%othergraduates$	0.8264	0.1597	0.7688	0.1298
	(0.6070)	(0.3455)	(0.6147)	(0.3345)
$InfofromCompetitors_{4dig,9496}$	0.5668	-0.0136	0.5958	-0.0015
	(0.4976)	(0.2803)	(0.4975)	(0.2845)
$Herfindahl_{4dig,t-1}$	76.6209	-28.7249	90.6908	-24.3421
	(28.8200)***	(14.8506)*	(30.7710)***	(15.7407)
$\Delta grossoutput_{4dig,98-00}$	-0.1638	-0.0457	-0.1416	0.0233
	(0.1609)	(0.0990)	(0.1642)	(0.1013)
Info from plant			0.6149	0.8863
			(0.2942)**	(0.1444)***
Info from group			0.3257	-0.2475
			(0.2046)	(0.1422)*
vertical Info			0.0804	0.0524
			(0.2845)	(0.1754)
Info from competitors			-0.0900	-0.3163
			(0.2496)	(0.1608)**
Commercial Info			0.2468	0.7244
			(0.2597)	(0.1622)***
free Info			-0.0593	0.3787
			(0.2647)	(0.1789)**
Info from regulation			0.1236	-0.1281
			(0.2265)	(0.1517)
Info from universities			-0.1750	0.5710
			(0.2706)	(0.1862)***
Info from government			-0.2014	-0.3284
			(0.2941)	(0.2010)

Notes: Number of observations is 1849 in all columns. Robust standard errors in parentheses, estimated allowing correlation between unobservables for plants in the same firm. Columns 2 and 4 report estimated coefficients of the propensity to innovate equation. Columns 1 and 3 report the estimated coefficients of the level of investment, conditional on having invested. Regressors included in all columns but not reported in the table are: 3 indicators for structural change (startup, merger and closure), 10 regional dummies and 3-digit industry dummies.

Appendix E

Appendix to Chapter 6

E.1 Variables description

Wages The Federal Employment Office requires plants to report any beginning and end of an employment relationship which is covered by social security. Employers have to provide information on ongoing relationships at the 31 of December every year. For each wage spell, the duration of which is calculated in calendar days, I observe the average daily wage and I deflate wages using the Consumer Price Index, with 1995 as the basis year. The exact individual wage in DM is reported, only for group with high wages the wages reported are censored. The defined threshold, the contribution assessment ceiling of the social insurance system, varies from year to year.

This limitation is not a serious problem for our sample: less than 1.5 % of all wage observations are top-coded.

The education group mostly affected by censoring are the university graduates, for them the percentage of censored wage observations becomes 11.7% and increases with years spent in the labour market with a peak of 25% at the 10th year of experience.

Size of plant This variable is defined as the number of employees as the 1st of June of each year. It is derived from the original 1% sample dataset.

Size Categories I have used different classification for the size categories according to the particular matter investigated. A first broader classification distinguishes among small (<100 employees), medium (100 to 1000 employees) and big (>1000

- Qualified services providers
- Simple Services provides
- Infrastructural tasks

Marital Status This dummy variable is equal to one if the worker is married

Number of past displacements I calculate this variable as the total number of times a worker, has lost his job because of plant closure, before the current job. I define a plant closure if a plant is recorded as having zero employees (and does not reappear in the sample).

Regional location This variable aggregates the 142 administrative districts (*Kreis*) of the Federal Employment Services in Western Germany in 11 regional units *(Laender)*.

Industry Classification This variable defines the specific industry to which the employing establishment belongs to. The data contains information at a very detailed level (85 categories). I exclude from our analysis the agricultural sector and I aggregate the other indsutries in the following categories:

- Energy, mining, water
- Chemical industry
- Metal industry, machines
- Electro technical industry, automobiles
- optical industry, fine mechanics
- wood, printing, paper
- leather, textiles, food
- construction, carpentry
- trade
- traffic, news
- credit and insurance

Table E.1: Incidence of top coding for University graduate by year of experience

	mean	Std. dev.	Obs
1	2.035	14.122	3685
2	5.084	21.970	4445
3	6.046	23.836	4350
4	7.845	26.891	4130
5	9.747	29.664	3755
6	13.302	33.964	3383
7	16.364	37.002	2866
8	18.573	38.897	2369
9	22.233	41.592	2015
10	24.045	42.748	1701

employees) plants. I then used a more detailed classification that includes 5 categories: 1-4 employees, 5-19 employees, 20-99 employees, 100-999 employees, and more than 1000. A further classification includes 8 categories: 1 employee, 2-10

Work experience I define actual work experience as the number of years (weeks) worked full-time from the year of labour market entry onwards. Hence, I assume that a worker doesn't accumulate any work experience while he holds a part-time job. Given the nature of the data, a problem arise with work experience acquired while self-employed or in the civil service, since these spells are not observed. Moreover I assume that apprentices only start cumulating experience after the end of their apprenticeship.

Tenure Tenure can be precisely measured by adding up the number of years (weeks) the worker was employed at the same plant, since plants must report the date the worker joined the firm as well as the date the worker left the firm, the measure of tenure is computed very precisely.

Education groups I mainly distinguish 3 education groups: "unskilled", "skilled" and "graduates". In fact, I aggregate from 5 categories: no formal education, some vocational education, vocational qualification, polytechnic degree and university degree.

The first group, "unskilled" includes: workers with no formal education and workers with some vocational education. I define workers with no formal education, those who never had a placement with a firm neither did an apprenticeship and do not hold any polytechnic or university degree. More precisely, unskilled workers

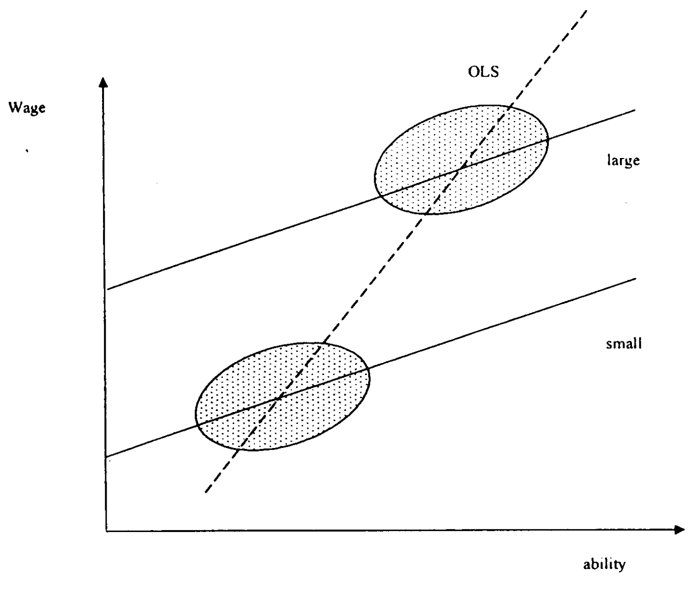
- services
- charities and public services

Past Growth Given the definition of size, I include the growth variable as the difference in log size between (t-1) and (t-2).

Age of the firm This variable is strongly censored: I know the exact date of "birth" for those plants which have been built after 1977, therefore I can only observe the exact age of the plant that have not been in business more than 18 years. This, I believed has flowed my analysis as far the wage age relationship is concerned. When I created age categories for the plants, I included those observations that were left censored in the category of plants "15 years or older".

E.2 Graphical description of model

Figure E.1: Previous models



were never reported as apprentices or as doing jobs for which a tertiary education degree was necessary. Workers with some vocational education, are workers who did some work placement with a firm but they have not completed an apprenticeship and were never classified as university or polytechnic graduates in any of the jobs they held.

The second group are the "skilled": workers who are reported as apprentice (*Praktikant*) in one company for at least 700 days, and workers with a work placement, if the work placement lasted 1 year or more and at least in half of the jobs the worker held he was recorded as a worker with a completed apprenticeship. Only spells after completion of the apprenticeship training are considered in the analysis.

The third group includes *Fachhochschule* graduates, workers who were recorded in at least one jobs as polytechnic graduates, but never as university graduates and university graduates, worker who were employed at least once in a job that classified them as university graduates. The difference between this last two categories lies in the duration of the course, with the university courses lasting longer, and in the more practical content of a *Fachhochschule* curriculum in respect to a more theoretical one of the university degree. Only wage spells after graduation are used in the analysis.

Occupational Group This variable describes the field of occupational specialization of an employee. I aggregate the very detailed information available in the data (269 categories) up to include 11 occupational groups.

- Miners
- Row materials and Intermediate Goods Producers
- Consumption Goods Producers
- Builders: main building
- Builders: renovation
- Installation and maintenance of machinery
- Planning and Organisation, Laboratory Technicians
- Administration
- Qualified Administrative and Managers

Figure E.2: A comparative Advantage Model: Gibbons and Katz, 1992

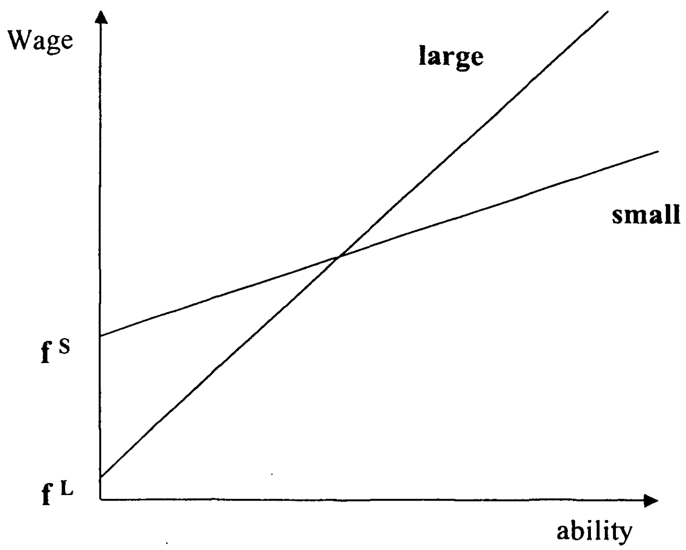


Figure E.3: The model: a graphical intuition

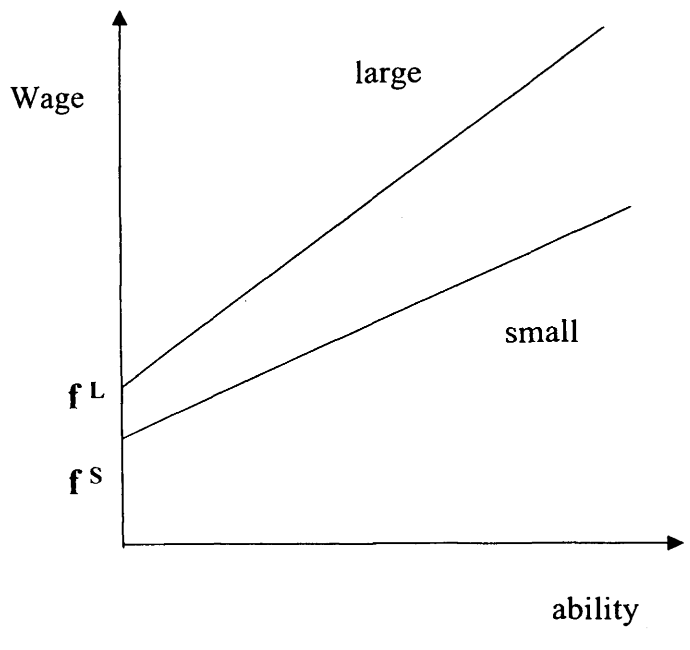


Table E.2: Size elasticities across education groups:unskilled

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(size)	0.05722	0.04852	0.03001	0.04093	0.00823	0.01454	0.02649	0.00932	0.01389
	(0.00251)***	(0.00215)***	(0.00174)***	(0.00177)***	(0.00440)*	(0.00693)**	(0.00187)***	(0.00480)*	(0.00479)***
semiskilled		0.07737					-0.06120		
		(0.00593)***					(0.00972)***		
experience 1 year		0.13629	0.04665	0.13765	0.03062	0.05075	-0.03114	0.02664	0.03807
		(0.00568)***	(0.00604)***	(0.00658)***	(0.00606)***	(0.01043)***	(0.01108)***	(0.01030)***	(0.00741)***
experience 2 years		0.21842	0.05822	0.21869	0.02670	0.05060	-0.00811	0.02205	0.05932
		(0.00677)***	(0.01011)***	(0.00935)***	(0.01082)**	(0.01892)***	(0.01388)	(0.02010)	(0.01287)***
experience 3 years		0.26446	0.03855	0.26167	-0.00973	0.00655	-0.00017	-0.01641	0.03873
		(0.00794)***	(0.01362)***	(0.01211)***	(0.01553)	(0.02726)	(0.01567)	(0.03039)	(0.01888)**
experience 4 years		0.29723	0.00310	0.27645	-0.06454	-0.06371	-0.20457	-0.07231	-0.00520
		(0.00920)***	(0.01703)	(0.01462)***	(0.02049)***	(0.03589)*	(0.02080)***	(0.04042)*	(0.02475)
experience 5 year		0.26682	-0.05494	0.25061	-0.14475	-0.16341	-0.34346	-0.13333	-0.08032
		(0.01500)***	(0.02361)**	(0.02032)***	(0.02729)***	(0.04609)***	(0.03497)***	(0.04914)***	(0.03195)**
tenure 1 year		-0.01347	-0.03158	-0.03434	0.02339	0.03199	0.19486	0.02309	0.01921
		(0.00591)**	(0.00446)***	(0.00511)***	(0.00525)***	(0.00891)***	(0.01063)***	(0.01001)**	(0.00665)***
tenure 2 years		-0.00611	-0.03297	-0.02916	0.07696	0.10881	0.22239	0.05701	0.07712
		(0.00743)	(0.00769)***	(0.00740)***	(0.01004)***	(0.01626)***	(0.01394)***	(0.01969)***	(0.01186)***
tenure 3 years		0.02088	-0.02489	-0.01597	0.13072	0.19150	0.23886	0.08814	0.14523
		(0.00865)**	(0.01100)**	(0.01111)	(0.01560)***	(0.02505)***	(0.01737)***	(0.02975)***	(0.01718)***
tenure 4 years		0.01654	-0.03046	-0.02039	0.16809	0.25654	0.24503	0.09962	0.20081
		(0.01165)	(0.01381)**	(0.01495)	(0.02051)***	(0.03428)***	(0.03476)***	(0.03969)**	(0.02375)***
tenure 5 years		0.04251	-0.03486	0.00360	0.21212	0.33995	0.23011	0.11567	0.27789
		(0.03840)	(0.02970)	(0.03937)	(0.03400)***	(0.06370)***	(0.13623)*	(0.05159)**	(0.04665)***
plant's % skilled workers		0.00040	0.00031	0.00018	0.00005	-0.00004	0.00033	-0.00000	-0.00020
		(0.00013)***	(0.00010)***	(0.00011)	(0.00019)	(0.00037)	(0.00016)**	(0.00021)	(0.00022)
plant's % high skilled workers		0.00159	0.00079	0.00085	-0.00000	0.00005	0.00150	-0.00009	-0.00024
		(0.00090)*	(0.00060)	(0.00062)	(0.00067)	(0.00099)	(0.00084)*	(0.00076)	(0.00086)
$\widehat{lambda}$								-0.05852	-0.01837
								(0.01486)***	(0.00204)***
age							0.00197		
							(0.00176)		
married							0.01650		
							(0.01283)		
with children							0.02867		
							(0.02057)		
1 exogenous job loss							-0.12346		
							(0.01353)***		
2 exogenous job losses							-0.16530		
							(0.03086)***		
3 exogenous job losses							-0.22304		
							(0.07271)***		
4 exogenous job losses							-0.26193		
							(0.05599)***		
Observations	36541	36541	30536	36541	19584	36541	28831	19403	28831

Notes: The sample used for estimation in this table only includes unskilled and semikilled workers. Robust standard errors in parentheses, estimated allowing correlation between unobservables for workers in the same firm. All regressions include include year and occupation dummies. The sample used in the regression only includes the first 5 years of labour market experience of all education groups. The first column of the table reports results from a pooled level regression where I only include $ln(size)$, region and time dummies. In column 2 I include observable plants' and workers' characteristics as I did in column 5 of table 6.4. Columns 3 and 4 report longitudinal estimates, first difference (column 3) and fixed effects (column 4) within and across firms. Column 5 reports within firm first difference estimates and column 6 fixed effects estimates. Column 7 reports marginal effects from the probit mobility equation and finally columns 8 and 9 report within firm first difference and fixed effects estimates, respectively, that correct for non random mobility. *

Table E.3: Size elasticities across education groups:workers with apprenticeship qualification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(size)	0.03925	0.03484	0.02208	0.02804	0.01120	0.01643	0.02508	0.01236	0.01704
	*(0.00083)******	*(0.00094)******	*(0.00084)******	*(0.00075)******	*(0.00152)******	*(0.00219)******	*(0.00089)******	*(0.00195)******	*(0.00190)******
experience 1 year		0.06924	0.00086	0.05160	0.00321	0.00875	0.00620	0.00346	0.01085
		*(0.00223)******	*(0.00233)*	*(0.00239)******	*(0.00252)*	*(0.00342)****	*(0.00556)*	*(0.00847)*	*(0.00255)******
experience 2 years		0.11105	-0.01440	0.07409	-0.00538	0.00187	-0.01102	-0.00518	0.01382
		*(0.00273)******	*(0.00390)******	*(0.00354)******	*(0.00451)*	*(0.00599)*	*(0.00727)*	*(0.01323)*	*(0.00430)****
experience 3 years		0.14354	-0.03742	0.08793	-0.01765	-0.00850	-0.05804	-0.01623	0.01350
		*(0.00341)******	*(0.00551)******	*(0.00472)******	*(0.00661)******	*(0.00860)*	*(0.00946)******	*(0.01887)*	*(0.00605)****
experience 4 years		0.16213	-0.06201	0.09807	-0.03598	-0.02539	-0.24893	-0.03161	0.00675
		*(0.00438)******	*(0.00726)******	*(0.00607)******	*(0.00888)******	*(0.01125)****	*(0.01544)******	*(0.02512)*	*(0.00801)*
experience 5 years		0.16194	-0.10783	0.07573	-0.07372	-0.06151	-0.43776	-0.05516	-0.02093
		*(0.00955)******	*(0.01103)******	*(0.01033)******	*(0.01458)******	*(0.01768)******	*(0.03294)******	*(0.03263)**	*(0.01297)*
tenure 1 year		0.02831	-0.01085	-0.00282	0.00651	0.01428	0.12525	0.00536	0.01095
		*(0.00209)******	*(0.00169)******	*(0.00176)*	*(0.00217)******	*(0.00301)******	*(0.00527)******	*(0.00710)*	*(0.00231)******
tenure 2 years		0.02993	-0.01824	-0.01236	0.00934	0.02602	0.15729	-0.00028	0.01688
		*(0.00281)******	*(0.00272)******	*(0.00242)******	*(0.00395)****	*(0.00518)******	*(0.00675)******	*(0.01123)*	*(0.00389)******
tenure 3 years		0.02708	-0.02187	-0.02097	0.01099	0.03862	0.13051	-0.01015	0.02392
		*(0.00382)******	*(0.00397)******	*(0.00329)******	*(0.00593)**	*(0.00753)******	*(0.00992)******	*(0.01642)*	*(0.00569)******
tenure 4 year		0.02963	-0.03423	-0.03873	0.00687	0.04498	0.07330	-0.02496	0.02579
		*(0.00604)******	*(0.00595)******	*(0.00520)******	*(0.00863)*	*(0.01042)******	*(0.02479)******	*(0.02241)*	*(0.00822)******
tenure 5 year		0.06981	-0.03637	-0.02352	0.00197	0.06816	-0.02010	-0.04014	0.04469
		*(0.02187)******	*(0.01515)****	*(0.01912)*	*(0.01800)*	*(0.02543)******	*(0.15845)*	*(0.03127)*	*(0.01848)****
plant's % skilled workers		0.00096	0.00040	0.00053	0.00014	0.00013	0.00101	0.00016	0.00013
		*(0.00006)******	*(0.00005)******	*(0.00005)******	*(0.00006)****	*(0.00009)*	*(0.00009)******	*(0.00007)****	*(0.00008)**
plant's % high skilled workers		0.00254	0.00150	0.00154	0.00010	0.00025	0.00224	0.00008	0.00009
		*(0.00028)******	*(0.00022)******	*(0.00023)******	*(0.00022)*	*(0.00035)*	*(0.00039)******	*(0.00034)*	*(0.00026)*
$\widehat{lambda}$								-0.03462	-0.00673
								*(0.00980)******	*(0.00094)******
age							0.01316		
							*(0.00115)******		
married							0.01429		
							*(0.00636)****		
with children							0.03990		
							*(0.01181)******		
1 exogenous job loss							-0.16231		
							*(0.00734)******		
2 exogenous job losses							-0.19671		
							*(0.02349)******		
3 exogenous job losses							-0.25800		
							*(0.04682)******		
4 exogenous job losses							-0.42032		
							*(0.17458)****		
5 exogenous job losses							-0.32257		
							*(0.13576)****		
Observations	131514	131514	108889	131514	80639	131514	105214	80256	105214

Notes: The sample used for estimation in this table only includes workers with an apprenticeship qualification. Robust standard errors in parentheses, estimated allowing correlation between unobservables for workers in the same firm. All regressions include include year and occupation dummies. The sample used in the regression only includes the first 5 years of labour market experience of all education groups. The first column of the table reports results from a pooled level regression where I only include $ln(size)$, region and time dummies. In column 2 I include observable plants' and workers' characteristics as I did in column 5 of table 6.4. Columns 3 and 4 report longitudinal estimates, first difference (column 3) and fixed effects (column 4) within and across firms. Column 5 reports within firm first difference estimates and column 6 fixed effects estimates. Column 7 reports marginal effects from the probit mobility equation and finally columns 8 and 9 report within firm first difference and fixed effects estimates, respectively, that correct for non random mobility. * significantly different from zero at the 10 percent level. ** significantly different from zero at the 5 percent level. *** significantly different from zero at the 1 percent level.

Table E.4: Size elasticities across education groups:University and Fachochschule gr

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(size)	0.03755	0.03137	0.01350	0.01886	0.00745	0.01123	0.02353
	*(0.00172)******	*(0.00196)******	*(0.00270)******	*(0.00226)******	*(0.00330)****	*(0.00504)****	*(0.00232)****
university graduates		0.08719					-0.05429
		*(0.00727)******					*(0.01217)****
experience 1 year		0.08641	0.01036	0.07085	0.00802	0.02580	-0.02694
		*(0.00718)******	*(0.00526)****	*(0.00725)******	*(0.00558)*	*(0.00776)******	*(0.01569)*
experience 2 years		0.12682	-0.01035	0.09449	-0.00549	0.01997	-0.04330
		*(0.00923)******	*(0.00893)*	*(0.01199)******	*(0.01066)*	*(0.01453)*	*(0.01996)**
experience 3 years		0.16321	-0.03180	0.11197	-0.01976	0.01222	-0.04330
		*(0.01012)******	*(0.01223)******	*(0.01664)******	*(0.01525)*	*(0.02147)*	*(0.02400)*
experience 4 years		0.19444	-0.06639	0.11442	-0.04225	-0.00418	-0.15436
		*(0.01097)******	*(0.01605)******	*(0.02090)******	*(0.02045)****	*(0.02880)*	*(0.03833)**
experience 5 years		0.19236	-0.12189	0.05652	-0.09540	-0.04452	-0.37123
		*(0.01913)******	*(0.02123)******	*(0.02827)****	*(0.02658)******	*(0.03918)*	*(0.10214)**
tenure 1 year		0.01258	-0.02513	-0.02590	-0.00726	0.01366	0.02213
		*(0.00627)****	*(0.00424)******	*(0.00483)******	*(0.00525)*	*(0.00702)**	*(0.01442)*
tenure 2 years		0.01700	-0.03100	-0.03974	-0.00548	0.02965	0.04712
		*(0.00834)****	*(0.00702)******	*(0.00699)******	*(0.00980)*	*(0.01290)****	*(0.01846)**
tenure 3 years		0.00814	-0.04411	-0.05647	-0.01002	0.04277	0.02124
		(0.01050)	*(0.00949)******	*(0.00970)******	*(0.01406)*	*(0.01928)****	*(0.02495)*
tenure 4 year		-0.01532	-0.05585	-0.07791	-0.01791	0.04599	-0.18212
		(0.01358)	*(0.01269)******	*(0.01234)******	*(0.01907)*	*(0.02633)**	*(0.06416)**
tenure 5 year		-0.04008	-0.07241	-0.09983	-0.04431	0.00487	0.11251
		(0.05224)	*(0.03315)****	*(0.04631)****	*(0.03551)*	*(0.05814)*	*(0.10722)*
plant's % skilled workers		0.00095	-0.00006	0.00038	0.00002	-0.00001	0.00064
		*(0.00026)******	*(0.00028)*	*(0.00027)*	*(0.00030)*	*(0.00038)*	*(0.00036)*
plant's % high skilled workers		0.00166	0.00042	0.00068	0.00017	0.00001	0.00120
		*(0.00027)******	*(0.00029)*	*(0.00027)****	*(0.00029)*	*(0.00039)*	*(0.00035)****
$\widehat{lambda}$						4.64331	
						*(0.14627)******	
age							0.00936
							*(0.00228)****
married							0.03321
							*(0.01093)****
with children							0.00782
							(0.02354)
1 exogenous job loss							-0.20370
							*(0.03660)****
2 exogenous job losses							-0.06871
							(0.07352)
Observations	14776	14776	11749	14776	9966	14776	11507
	0.189	0.370	0.10	0.82	0.07	0.92	

Notes: The sample used for estimation in this table only includes workers with a degree from a university or a Fachochschule. Robust standa allowing correlation between unobservables for workers in the same firm. All regressions include include year and occupation dummies. The sa includes the first 5 years of labour market experience of all education groups. The first column of the table reports results from a pooled level *ln(size)*, region and time dummies. In column 2 I include observable plants' and workers' characteristics as I did in column 5 of table 6.4. Col estimates, first difference (column 3) and fixed effects (column 4) within and across firms. Column 5 reports within firm first difference estima estimates. Column 7 reports marginal effects from the probit mobility equation and finally columns 8 and 9 report within firm first difference respectively, that correct for non random mobility. * significantly different from zero at the 10 percent level. ** significantly different from zero significantly different from zero at the 1 percent level.